#### Fifth SimLab Short Course on

## **Parallel Numerical Simulation**

Belgrade, October 1-7, 2006

Iterative Solution of Linear Systems

October 3, 2006

Hans-Joachim Bungartz Department of Computer Science – Chair V Technische Universität München, Germany



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and ...

Tools for Algorithm . . .

Literature

Page 1 of 30

#### 3.1. Standard Iterative Solvers of SLE

- iterative solution of large linear systems is one of the most important numerical tasks in scientific computing (they occur in the discretization of both ODE and PDE)
- direct solvers are often not competitive:
  - too large number of unknowns (cf. PDE in 3D)
  - sparse matrices (classical elimination destroys sparsity)
  - anyway only approximations, thus no need for exact solution (this holds esp. in the nonlinear case, where a system of linear equations occurs in each step of some outer iteration for the nonlinearity)
- objective: "for 3 digits, you need 10 steps" no matter how big the number n of unknowns is
- however typically: speed of convergence deteriorates with increasing n!



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 2 of 30

## **Principal Remarks on Iterations**

• consider an iterative scheme, starting from  $x^{(0)}$ , and, hopefully converging to the solution x of Ax = b:

$$x^{(0)} \to x^{(0)} \to \cdots \to x^{(i+1)} \to \cdots \to \lim_{i \to \infty} x^{(i)} = x$$

- speed of convergence:  $\|x-x^{(i+1)}\|<\gamma\cdot\|x-x^{(i)}\|$  for some  $0<\gamma<1$
- typical behaviour of iterative schemes:

$$\gamma = O(1 - n^{-k}), \ k \in \{0, 1, 2, \dots\}$$

- strategy: look for iterative methods with
  - only O(n) arithmetic operations per step of iteration (cost)
  - a convergence behaviour like  $\gamma < 1 {\sf const} \ll 1$
- two big families: relaxation and Krylov subspace methods



#### Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

## **Relaxation Techniques 1**

- sometimes also called smoothing methods:
  - Richardson iteration
  - Jacobi iteration
  - Gauß-Seidel iteration
  - successive over relaxation (SOR) or damped methods
- All start from the residual r after i steps of iteration:

$$r^{(i)} = b - Ax^{(i)} = Ax - Ax^{(i)} = A(x - x^{(i)}) = -Ae^{(i)}$$

(the error e is not known, so r is used as an indicator)

- How to obtain an improvement?
  - Richardson: use the residual as it is as a correction
  - Jacobi/Gauß-Seidel: make one component of r vanish
  - SOR/damped: same, but do a bit less/more than indicated



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 4 of 30

## **Relaxation Techniques 2**

Richardson iteration:

repeat(i): for 
$$k = 1, ..., n$$
 do  $x_k^{(i+1)} = x_k^{(i)} + r_k^{(i)}$ 

• (damped) Jacobi iteration:

repeat
$$(i)$$
: for  $k=1,\ldots,n$  do  $y_k=r_k^{(i)}/a_{k,k}$  for  $k=1,\ldots,n$  do  $x_k^{(i+1)}=x_k^{(i)}+\alpha\cdot y_k$ 

(compute and store updates, apply them at the end)

• Gauß-Seidel or SOR, resp.:

$$\begin{array}{l} \mathsf{repeat}(i): \; \mathsf{for} \; k = 1, \dots, n \; \mathsf{do} \\ r_k^{(i)} \; := \; b_k - \sum_{j=1}^{k-1} a_{kj} x_j^{(i+1)} - \sum_{j=k}^n a_{kj} x_j^{(i)} \\ y_k \; := \; \frac{1}{a_{kk}} \cdot r_k^{(i)}, \quad x_k^{(i+1)} \; := \; x_k^{(i)} + \alpha \cdot y_k \end{array}$$

(compute same updates, but apply them at once)

• For an analysis, decompose A in its strictly lower, diagonal, and strictly upper part:  $A = L_A + D_A + U_A$ 



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 5 of 30

## **Relaxation Techniques 3**

• all can be written in the form  $Mx^{(i+1)} + (A-M)x^{(i)} = b$  or

$$x^{(i+1)} = M^{-1}b - (M^{-1}A - I)x^{(i)} = x^{(i)} + M^{-1}r^{(i)}$$

- how looks M?
  - Richardson: M := I,
  - Jacobi:  $M := D_A$ ,
  - Gauß-Seidel:  $M := D_A + L_A$ ,
  - SOR:  $M := \frac{1}{\alpha}D_A + L_A$ .
- some convergence results:
  - If the iteration converges at all, then towards x.
  - The crucial quantity is the *spectral radius* of  $-M^{-1} \cdot (A-M)$  which is smaller than 1 if and only if the iteration converges.
  - necessary for SOR:  $0 < \alpha < 2$
  - sufficient for Gauß-Seidel/SOR: A positive definite
  - sufficient for Jacobi: both A and  $2D_A A$  are positive definite



#### Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 6 of 30

## 3.2. Towards Krylov: Steepest Descent

• alternative point of view for positive definite *A*:

$$x$$
 solves  $Ax = b \Leftrightarrow x$  minimizes  $f(x) = 0.5 \cdot x^T Ax - b^T x + c$ 

(uniqueness of minimum due to positive definiteness)

- hence new strategy: look for minimum of f
- possible way: method of steepest descent (looks for the best improvement in the direction of the negative gradient)

$$\mathsf{repeat}(i): \alpha_i = \frac{r^{(i)^T}r^{(i)}}{r^{(i)^T}Ar^{(i)}}; x^{(i+1)} = x^{(i)} + \alpha_i r^{(i)}; r^{(i+1)} = r^{(i)} - \alpha_i Ar^{(i)};$$

(1D minimization along search direction  $-f'(x^{(i)}) = r^{(i)}$ )

- even simpler: search along coordinate axes (is Gauß-Seidel!)
- slow convergence (progress may get lost again!)
- crucial quantity: spectral condition number of A

$$\kappa(A) = \frac{\lambda_{\max}(A)}{\lambda_{\min}(A)}$$



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 7 of 30

## **Improvement: Conjugate Directions**

- further enhancement:
  - orthogonal search directions, error after i steps shall be orthogonal to all previous search directions
  - nothing destroyed, hence: in principle a direct method
  - however, since n iterations are too much in practice: used as an iterative method (therefore called *semi-iterative* method)
  - new search directions:  $x^{(i+1)} = x^{(i)} + \alpha_i d^{(i)}$
  - optimum orthogonality:  $0 = d^{(i)^T} e^{(i+1)}$ , but error is missing
  - therefore *conjugation*:  $0 = d^{(i)^T} A e^{(i+1)}$  (u and v are called *A-orthogonal* or *conjugate*, if  $u^T A v = 0$ )
  - algorithm: start with  $d^{(0)} = r^{(0)}$  and iterate:

$$\begin{aligned} \mathsf{repeat}(i) : \alpha_i &= \frac{d^{(i)^T} r^{(i)}}{d^{(i)^T} A d^{(i)}}; x^{(i+1)} = x(i) + \alpha_i d^{(i)}; \\ r^{(i+1)} &= r^{(i)} - \alpha_i A d^{(i)}; \end{aligned}$$

– still to be done: construction of the conjugate directions  $d^{(i)}$ 



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 8 of 30

## **Finally: Conjugate Gradients**

- above method + efficient construction of the conjugate directions
- · principle of construction: Gram-Schmidt conjugation of r's
- no detailed derivation here, just the algorithm:

$$\begin{split} \mathsf{repeat}(i) : & \alpha_i = \frac{d^{(i)^T} r^{(i)}}{d^{(i)^T} A d^{(i)}}; \\ & x^{(i+1)} = x^{(i)} + \alpha_i d^{(i)}; \\ & r^{(i+1)} = r^{(i)} - \alpha_i A d^{(i)}; \\ & \beta_{i+1} = \frac{r^{(i+1)^T} r^{(i+1)}}{r^{(i)^T} r^{(i)}}; \\ & d^{(i+1)} = r^{(i+1)} + \beta_{(i+1)} d^{(i)}; \end{split}$$

- faster than steepest descent, but still depending on n!
- search spaces form a so-called Krylov sequence:

$$\begin{split} \mathrm{span}\{d^{(0)},\dots,d^{(i-1)}\} &= \mathrm{span}\{d^{(0)},Ad^{(0)},\dots,A^{i-1}d^{(0)}\} \\ &= \mathrm{span}\{r^{(0)},Ar^{(0)},\dots,A^{i-1}r^{(0)}\} \end{split}$$

• other famous Krylov methods: GMRES, Bi-CGSTAB



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and ...

Tools for Algorithm . . .

Literature

Page 9 of 30

# 3.3. Fast Iterative Solvers of Systems of Linear Equations

- crucial drawback of solvers discussed so far: they become slower if we discretize more accurate!
- now: look for possible remedies
  - relaxation: explicit application of the multigrid principle
  - Krylov/cg: preconditioning (typically also following multigrid)
- · let us start with preconditioning:
  - crucial quantity for cg's convergence: condition number
  - PDE: condition of system matrix increases dramatically with
  - therefore: look for a modified matrix with better condition

$$Ax = b \Leftrightarrow M^{-1}Ax = M^{-1}b \Leftrightarrow W^{-1}AW^{-T}y = W^{-1}b,$$

#### where

M s.p.d.,  $WW^T=M,\ y=W^Tx,\ M^{-1}A$  and  $W^{-1}AW^{-T}$  similar (no need to construct M or W explicitly, must be applied only)



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers...

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 10 of 30

## **Strategies for Preconditioners**

- the simplest choice: M = I (cheap, but useless)
- the best choice: M = A (perfect, but expensive)
- some possibilities in-between:
  - diagonal or Jacobi preconditioner:  $M = D_A$
  - GS or SOR are not used due to lack of symmetry
  - SSOR preconditioner:

$$M^{(1/2)} = \alpha^{-1}D_A + L_A; \ M^{(1)} = \alpha^{-1}D_A + U_A;$$
$$M = \frac{\alpha}{\alpha - 2} \left(M^{(1/2)}\right)^{-1} D_A^{-1} M^{(1)}$$

- incomplete factorization, e.g. ILU: compute approximate factors L and U instead of exact ones in direct methods
- **sparse approximate inverse**: look for some cheap B with

$$\min_{B} ||I - AB||^2, \ M^{-1} = B$$

- multilevel preconditioners: following the multigrid principle



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers...

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 11 of 30

## **The Multigrid Principle**

- starting point: Fourier mode analysis of the errors
  - decompose the error  $e^{(i)}=x^{(i)}-x$  into its Fourier components (Fourier transform)
  - observe how they change/decrease under a standard relaxation like Jacobi or Gauß-Seidel (in a two-band sense):
    - \* The *high* frequency part (with respect to the underlying grid) is reduced quite quickly.
    - \* The *low* frequency part (w.r.t. the grid) decreases only very slowly; actually the slower, the finer the grid is.
  - This behaviour is annoying
    - the low frequencies are not expected to make troubles, but we can hardly get rid of them on a fine grid;

#### but also encouraging

\* the low frequencies can be represented and, hopefully tackled, on a coarser grid – there is no need for the fine resolution.



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers...

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 12 of 30

## A Simple Example

- 1D Laplace equation, u(0) = u(1) = 0 (exact solution 0)
- equidistant grid, 65 points, 3-point stencil, damped Jacobi method with damping parameter 0.5
- start with random values in [0,1] for u in the grid points
- After 100 (!) steps, there is still a maximum error bigger than 0.1 due to low-frequency components!
- therefore the name *smoothers* for relaxation schemes:
  - They reduce the strongly oscillating parts of the error quite efficiently.
  - They, thus, produce a **smooth** error which is very resistent.
- the idea: work on grids of different resolution



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

#### **Coarse Grid Correction 1**

sequence of equidistant grids on our domain:

$$\Omega_l, \ l=1,2,\ldots,L,$$
 with mesh width  $h_l=2^{-l}$ 

- let  $A_l, b_l, \ldots$  denote corresponding matrix, right-hand side,...
- combine work on two grids with a *correction scheme*:

```
smooth the current solution x_l; form the residual r_l = b_l - A_l x_l; restrict r_l to the coarse grid \Omega_{l-1}; provide a solution to A_{l-1} \, e_{l-1} = r_{l-1}; prolongate e_{l-1} to the fine grid \Omega_l; add the resulting correction to x_l; if necessary, smooth again ;
```



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 14 of 30

#### **Coarse Grid Correction 2**

- the different steps of this 2-grid algorithm:
  - the pre-smoothing: reduce high-frequency error components, smooth error, and prepare residual for transfer to coarse grid
  - the restriction: transfer from fine grid to coarse grid
    - \* injection: inherit the coarse grid values and forget the others
    - \* (full) weighting: apply some averaging process
  - the coarse grid correction: provide an (approximate) solution on the coarse grid (direct, if coarse enough; some smoothing steps otherwise)
  - the prolongation: transfer from coarse grid to fine grid
    - \* usually some interpolation method
  - the post-smoothing: sometimes reasonable to avoid new high-frequency error components
- recursive application leads to multigrid methods



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 15 of 30

## The V-Cycle

• now, the coarse grid equation is solved by coarse grid correction, too; the resulting algorithmic scheme is called *V-cycle*:

```
SimLab
```

```
smooth the current solution x_l; form the residual r_l = b_l - A_l x_l; restrict r_l to the coarse grid \Omega_{l-1}; solve A_{l-1} e_{l-1} = r_{l-1} by coarse grid correction; prolongate e_{l-1} to the fine grid \Omega_l; add the resulting correction to x_l; if processory smooth again:
```

if necessary, smooth again ;

on the finest grid: direct solution

number of smoothing steps: typically small (1 or 2)

Towards Krylov:...

Fast Iterative Solvers...

Standard Iterative . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 16 of 30

## **Multigrid Algorithms**

- the V-cycle is not the only multigrid scheme:
  - the W-cycle: after each prolongation, visit the coarse grid once more, before moving on to the next finer grid
  - the **nested iteration**: start on coarsest grid  $\Omega_1$ , smooth, prolongate to  $\Omega_2$ , smooth, prolongate to  $\Omega_3$ , and so on, until finest grid is reached; now start V-cycle
  - full multigrid: replace 'smooth steps above by 'apply a Vcycle; combination of improved start solution and multigrid solver
- multigrid idea is not limited to rectangular or structured grids: we just need a hierarchy of nested grids (works for triangles or tetrahedra, too)
- also without underlying geometry: algebraic multigrid



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

## **Basic Convergence Results**

- Cost (storage and computing time):
  - 1D:  $c \cdot n + c \cdot n/2 + c \cdot n/4 + c \cdot n/8 + \dots \le 2c \cdot n = O(n)$
  - **2D:**  $c \cdot n + c \cdot n/4 + c \cdot n/16 + c \cdot n/64 + \cdots \le 4/3c \cdot n = O(n)$
  - 3D:  $c \cdot n + c \cdot n/8 + c \cdot n/64 + c \cdot n/512 + \dots \le 8/7c \cdot n = O(n)$
  - i.e.: work on coarse grids is negligible compared to finest grid
- Benefit (speed of convergence):
  - always significant acceleration compared with pure use of smoother (relaxation method)
  - in most cases even ideal behaviour  $\gamma = O(1 \mathsf{const})$
  - effect:
    - \* constant number of multigrid steps to obtain a given number of digits
    - $\star$  overall computational work increases only linearly with n



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers..

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 18 of 30

#### 3.4. Tools: Libraries and Software

- In addition to standard tools like editors, compilers, or debuggers, there is a lot of (commercial or public domain) support available:
  - Modelling: Computer algebra programs like Mathematica, Maple, Axiom, or Reduce support derivations and proofs of theorems via symbolic means.
  - Numerics: Mathematica, Maple, or MATLAB support the development, testing, and analysis of (numerical) algorithms and allow an efficient prototyping.
  - Implementation: A zoo of (numerical) libraries provide upto-date modules for standard tasks (numerical linear algebra etc.), tailored to specific target architectures.
  - Visualization: Packages like IDL, IRIS Explorer, or AVS/Express offer (nearly) all you want.



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 19 of 30

- GAMS: Guide to Available Mathematical Software
  - service offered by the National Institute of Standards & Technology
  - see http://gams.nist.gov/
  - catalogue and database of more than 100 packages and libraries with together several tens of thousands of routines
  - Topics range from number theory to statistics!
  - majority: FORTRAN programs for numerical tasks (systems of linear equations, eigenvalues, roots, differential equations, ...)
  - includes both public domain material (at NIST or at NETLIB, see below) and commercial (licenced) products.
  - good user guidance



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 20 of 30

- Matrix market
  - see http://math.nist.gov/MatrixMarket/
  - repository of test data for use in comparative studies of algorithms for numerical linear algebra
  - features nearly 500 (sparse) matrices from various fields of applications (chemical engineering, fluid flow, power system networks, quantum physics, or structural engineering, e.g.)
  - provides also matrix generation tools
  - classification according to matrix properties:
    - \* number field: real or complex
    - \* nonzero structure: dense, banded sparse, tridiagonal, ...
    - \* symmetry: none, symmetric, skewsymmetric, SPD, SSPD,...
    - \* shape: square, more rows than columns,...



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 21 of 30

- NETLIB: repository of free software for numerical purposes
  - see http://www.netlib.org/
  - offered by University of Tennessee and Oak Ridge Nat'l Lab
  - several mirrored copies all over the world
  - about 135 million requests since 1985, > 40 million in 2000
  - > 90% http, rest ftp and email
  - about 160 different libraries, among which
    - \* BLAS (Basic Linear Algebra Subprograms)
    - \* LAPACK (Linear Algebra PACKage)
    - \* ODEPACK (ordinary differential equations)
    - \* MPI (message passing interface, for parallelization)
    - \* PLTMG (elliptic boundary value problems)



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 22 of 30

#### **BLAS**

- collection of robust, efficient, and portable modules for elementary vector and matrix operations
- basis for LAPACK routines, for example
- allows plug-and-play for numerical subroutines
- FORTRAN, to be used from FORTRAN/C/C++
- Java BLAS available, too
- levels:
  - Level 1: vector and vector-vector operations (norm, scalar product, vector addition, SAXPY, . . . )
  - Level 2 matrix-vector operations (rank-1-modifications, matrix-vector product, tridiagonal systems); vector processors
  - Level 3 matrix-matrix operations; parallel computers!



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 23 of 30

#### LAPACK

- popular collection of FORTRAN subroutines for standard problems from numerical linear algebra like linear systems, regression, eigenvalues, SVD, . . .
- dense and band matrices (not general sparse ones)
- successor of EISPACK and LINPACK, tuning for modern microprocessors and supercomputer architectures (reduction of memory accesses, block operations, ...)
- LAPACK routines use BLAS modules
- variants:
  - LAPACK90, CLAPACK, LAPACK++
  - ScaLAPACK (MIMD systems, scalability!)



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers ...

Tools: Libraries and . . .

Tools for Algorithm...

Literature

Page 24 of 30

- Visual Numerics:
  - see http://www.vni.com
  - mathematical libraries
  - predecessor: IMSL (The Int'l Math. & Statist. Library)
- Diffpack:
  - offered by Numerical Objects, see <a href="http://www.nobjects.com">http://www.nobjects.com</a>
  - environment for the development of code for numerical simulation problems plus libraries of efficient routines
  - object-oriented concept, available for most UNIX platforms
- NAG (Numerical Algorithms Group):
  - see http://www.nag.co.uk/
  - non-profit software house, spin-off of Oxford University
  - FORTRAN/FORTRAN90/C/Parallel libraries;
  - AXIOM; IRIS Explorer (visualization); Fastflo (CFD and more)



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers ...

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 25 of 30

- Numerical Recipes:
  - see http://www.nr.com
  - book series The Art of Scientific Computing (CU Press)
  - sophisticated algorithms and their implementations
  - available for FORTRAN 77, FORTRAN 90, C, Pascal, . . .
  - corresponding software is licenced and commercial
  - about 350 routines for topics like
    - \* solution of linear systems
    - \* interpolation and extrapolation
    - \* numerical quadrature
    - \* differentiation and approximation
    - \* roots and extrema
    - \* eigenvalues, differential equations, and more



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 26 of 30

## 3.5. Tools for Algorithm Development

- Libraries offer tested and efficient (w.r.t. both storage and runtime) standard modules for competitive simulation codes (do something classical cheap!)
- Another problem is algorithm development (develop something new and cheaper!):
  - design of algorithms
  - testing and rapid prototyping
  - analysis (convergence behaviour etc.)
  - not yet: production runs, memory or runtime optimization
- widespread solutions:
  - computer algebra programs like Maple or Mathematica
  - MATLAB



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm...

Literature

Page 27 of 30

## **Maple**

- by Waterloo Maple Inc., a spin-off of the University of Waterloo in Ontario (see <a href="http://www.maplesoft.com">http://www.maplesoft.com</a>)
- originally a mere computer algebra program, today "interactive environment for mathematical problem solving and programming"



- symbolic computations, formula manipulation
- numerical computations with arbitrary accuracy
- 2D and 3D graphical output
- straightforward programming for algorithm development
- structure:

kernel + main library + mixed library + packages



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 28 of 30

#### **MATLAB**

- by The MathWorks (see <a href="http://www.mathworks.com/">http://www.mathworks.com/</a>)
- originally: primarily for use in (maths) education
- today: "high-performance numerical computation and visualization software", standard tool for scientific computing research groups:
  - development, prototyping, programming
  - computations
  - visualization
- singular success story: >500 employees, >100 countries, >2000 universities and research institutes
- structure: basic program plus a collection of specialized tool boxes



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm...

Literature

Page 29 of 30

#### References

- [1] Walter Gander and Jiři Hřebíček. Solving Problems in Scientific Computing Using Maple and MATLAB. Springer-Verlag, Berlin, Germany / Heidelberg, Germany / London, UK / etc., second edition, 1995.
- [2] Werner Krabs. Mathematische Modellierung. Eine Einführung in die Problematik. Teubner-Verlag, 1997.
- [3] Gene H. Golub and James M. Ortega. Scientific Computing and Differential Equations. Academic Press, Boston, MA, USA, 1992.
- [4] Jack J. Dongarra, Iain S. Duff, Danny C. Sorensen, and Henk A. van der Vorst. Numerical linear algebra for high-performance computers. Society for Industrial and Applied Mathematics (SIAM), Philadelphia, PA, USA, 1998.
- [5] Kai Hwang. Advanced Computer Architecture: Parallelism, Scalability, Programmability. McGraw-Hill, New York, 1993.
- [6] Michael Griebel, Thomas Dornseifer, and Tilman Neunhoeffer. Numerical Simulation in Fluid Dynamics: A Practical Introduction. Society for Industrial and Applied Mathematics (SIAM), Philadelphia, PA, USA, 1997.



Standard Iterative . . .

Towards Krylov:...

Fast Iterative Solvers . . .

Tools: Libraries and . . .

Tools for Algorithm . . .

Literature

Page 30 of 30