
Solving large scale eigenvalue problems in electronic structure calculations

C. Bekas

Comp. Science & Engineering Dept.
University of Minnesota, Twin Cities

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Introduction and Motivation

Computational Materials Science Target Problem

...predict the properties of materials...

How?

- ***AB INITIO calculations:*** Simulate the behavior of materials at the atomic level, by applying the basic laws of physics:
Quantum Mechanics

What do we (hope to) achieve?

- Explain the *experimentally established* properties of materials
- Engineer new materials with *desired properties*

Applications:...numerous (some include)

- Semiconductors, synthetic light weight materials
- Drug discovery, protein structure prediction
- Energy: alternative fuels

In this talk

- Introduction to the mathematical formulation of *ab initio* calculations...
- in particular...the Density Functional Theory (DFT)...formulation
- Identify the computationally intensive “spots”... *eigenvalue calculations*

Large scale eigenvalue problems are central...

- Symmetric/Hermitian problems
- very large number of eigenvalues/vectors required...so
- reorthogonalization (Gram-Schmidt) and synchronization (barrier/join) costs dominate...
- limiting the feasible size of molecules under study

Alternative...Automated Multilevel Substructuring (AMLS)

- Significantly limits reorthogonalization costs...
- can attack very large problems...when $O(1000)$ eigs. are required...

Mathematical Modelling: The Wave Function

We seek to find the *steady state* of the *electron distribution*

- Each **electron e_i** is described by a corresponding **wave function ψ_i** ...
- ψ_i is a function of space (r)...in particular it is determined by
 - The position r_k of all particles (including nuclei and electrons)
 - It is normalized in such a way that

$$\int |\psi_i(r)|^2 dr = 1$$

- **Max Born's probabilistic interpretation: Considering a region D , then**

$$Pr(\psi_i, D) = \int_D |\psi_i(r)|^2 dr$$

...describes the probability of electron e_i being in region D . Thus: the distribution of electrons e_i in space is defined by the wave function ψ_i

Mathematical Modelling: The Hamiltonian

Steady state of the electron distribution:

➤ *it is such that it minimizes the total energy of the molecular system...(energy due to dynamic interaction of all the particles involved because of the forces that act upon them)*

Hamiltonian H of the molecular system:

➤ *Operator that governs the interaction of the involved particles...*
 ➤ *Considering all forces between nuclei and electrons we have...*

$$H = H_{nucl} + H_e + U_{nucl} + V_{ext} + U_{ee}$$

H_{nucl} *Kinetic energy of the nuclei*

H_e *Kinetic energy of electrons*

U_{nucl} *Interaction energy of nuclei (Coulombic repulsion)*

V_{ext} *Nuclei electrostatic potential with which electrons interact*

U_{ee} *Electrostatic repulsion between electrons*

Mathematical Modelling: Schrödinger's Equation

Let the columns of Ψ :

$$\Psi = [\psi_1, \psi_2, \dots, \psi_N]$$

hold the wave functions corresponding the electrons...Then it holds that

$$H\Psi = \epsilon\Psi$$

- This is an eigenvalue problem...that becomes a usual...
- “algebraic” eigenvalue problem when we discretize ψ_i w.r.t. space (r)
- Extremely complex and nonlinear problem...since
- Hamiltonian and wave functions depend upon all particles...
- We can very rarely (only for trivial cases) solve it exactly...

Variational Principle (in simple terms!)

Minimal energy and the corresponding electron distribution amounts to calculating the smallest eigenvalue/eigenvector of the Schrödinger equation

Schrödinger's Equation: Basic Approximations

Multiple interactions of all particles...result to extremely complex Hamiltonian...which typically becomes huge when we discretize

Thus...a number of reasonable approximations/simplifications have been considered...with negligible effects on the accuracy of the modeling:

- **Born-Oppenheimer:** *Separate the movement of nuclei and electrons...the latter depends on the positions of the nuclei in a parametric way...(essentially neglect the kinetic energy of the nuclei)*
- **Pseudopotential approximation:** *Nucleus and surrounding core electrons are treated as one entity*
- **Local Density Approximation:** *If electron density does not change rapidly w.r.t. sparse (r)...then electrostatic repulsion U_{ee} is approximated by assuming that density is locally uniform*

Density Functional Theory

High complexity is mainly due to the **many-electron formulation** of *ab initio* calculations...is there a way to come up with an **one-electron formulation**?

Key Theory

DFT: Density Functional Theory (Hohenberg,Kohn,Sham)

- ✓ The total ground energy of a molecular system is a functional of the electronic density...(number of electrons in a cubic unit)
- ✓ The energy of a system of electrons is at a minimum if it is an exact density of the ground state!

- This is an existence theorem...the density functional always exists
- ...but the theorem does not prescribe a way to compute it...

- This energy functional is highly complicated...
- Thus approximations are considered...concerning:
 - Kinetic energy and
 - Exchange-Correlation energies of the system of electrons

Density Functional Theory: Formulation (1/2)

Equivalent eigenproblem:

$$[H_{e_i} + V_{tot}(r; \rho)]\psi_i(r) = \epsilon_i\psi_i(r)$$

 ψ_i

One electron wave function

 ϵ_i

Energy of the i-th state of the system

 H_{e_i}

Kinetic energy of electron e_i

 $V_{tot}(r; \rho)$

Total potential that acts on e_i at position r

$$\rho(r) = \sum_{occ} |\psi_i(r)|^2$$

Charge density at position r

Density Functional Theory: Formulation (2/2)

Furthermore:

$$V_{tot}(r; \rho) = V_{ion} + V_H + V_{xc}$$

V_{ion} Potential due to nuclei and core electrons

V_H Coulomb potential from valence electrons $\nabla^2 V_H = -4\pi\rho$

V_{xc} Exchange-Correlation potential... **function of the charge density ρ**

Non-linearity: *The new Hamiltonian depends upon the charge density ρ while ρ itself depends upon the wave functions (eigenvectors) ψ_i*

Some sort of iteration is required until convergence is achieved!

Self Consistent Iteration in PARSEC

Start with initial guess for $V_{tot}(r, \rho_0)$ and iterate

1. Solve $[H_{e_i} + V_{tot}(r; \rho_{k-1})]\psi_i(r) = \epsilon_i\psi_i(r)$
2. Update charge density $\rho_k(r) = \sum_{occ} \psi_i(r)^*\psi_i(r)$
3. Solve $\nabla^2 V_H = -4\pi\rho_k(r)$
4. Update $V_{tot}(r, \rho_k(r)) = V_{ion}(r) + V_H(r) + V_{xc}(\rho_k)$
5. Has V_{tot} converged? If yes then break
6. Update $V_{tot}(r, \rho_k) = \mathcal{F}(V_{tot}(r, \rho_k), V_{tot}(r, \rho_{k-1}))$

Calculate total energy, forces etc...

S.C.I in PARSEC: Computational Considerations

Start with initial guess for $V_{tot}(r, \rho_0)$ and iterate

1. Solve $[H_{e_i} + V_{tot}(r; \rho_{k-1})]\psi_i(r) = \epsilon_i\psi_i(r)$
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S.C.In PARSEC: Computational Considerations

Start with initial guess for $V_{tot}(r, \rho_0)$ and iterate

1. Solve $[H_{e_i} + V_{tot}(r; \rho_{k-1})]\psi_i(r) = \epsilon_i\psi_i(r)$
2. Update charge density $\rho_k(r) = \sum_{OCC} \psi_i(r)^*\psi_i(r)$

Conventional approach:

- *Solve the eigenvalue problem (1)...and compute the charge densities...*
- *This is a tough problem...many of the smallest eigenvalues...deep into the spectrum are required! Thus...*
- *efficient eigensolvers have a significant impact on electronic structure calculations!*

Alternative approach:

- *The eigenvectors ψ_i are required only to compute $\rho_k(r)$*
- *Can we instead approximate charge densities without eigenvectors...?*
- *Yes...!*

Computational Considerations in Applying Eigensolvers for Electronic Structure Calculations

The Eigenproblem

Hamiltonian Characteristics

- *Discretization: High-order finite difference scheme...leads to*
- *Large Hamiltonians! ...typically $N > 100K$...with significant...*
- *number of nonzero elements (NNZ) $> 5M$...*
- *Hamiltonian is **Symmetric/Hermitian**...thus the eigenvalues are real numbers...some smallest and some larger than zero.*

Eigenproblem Characteristics (why is this a tough case?)

- *We need the algebraically smallest (leftmost) eigenvalues (and vectors)*
- *How many? Typically a large number of them. Depending upon the molecular system under study:*
 - *for standard spin-less calculations $\rightarrow Si_xH_y: (4x + y)/2$*
 - *i.e. for the small molecule $Si_{34}H_{36}$ we need the 86 smallest eigenvalues...*
- *For large molecules, $x, y > 500$ (or for exotic entities...quantum dots) thousands of the smallest eigenvalues are required....*
- *Using current state of the-art-methods we need thousands of CPU hours on DOE supercomputers...and we have to do that many times!*

Methods for Eigenvalues (basics only!)

Eigenvalue Approximation from a Subspace

Consider the standard eigenvalue problem: $Ax = \lambda x$

and let V be a thin $N \times k$ ($N \gg k$) matrix...then

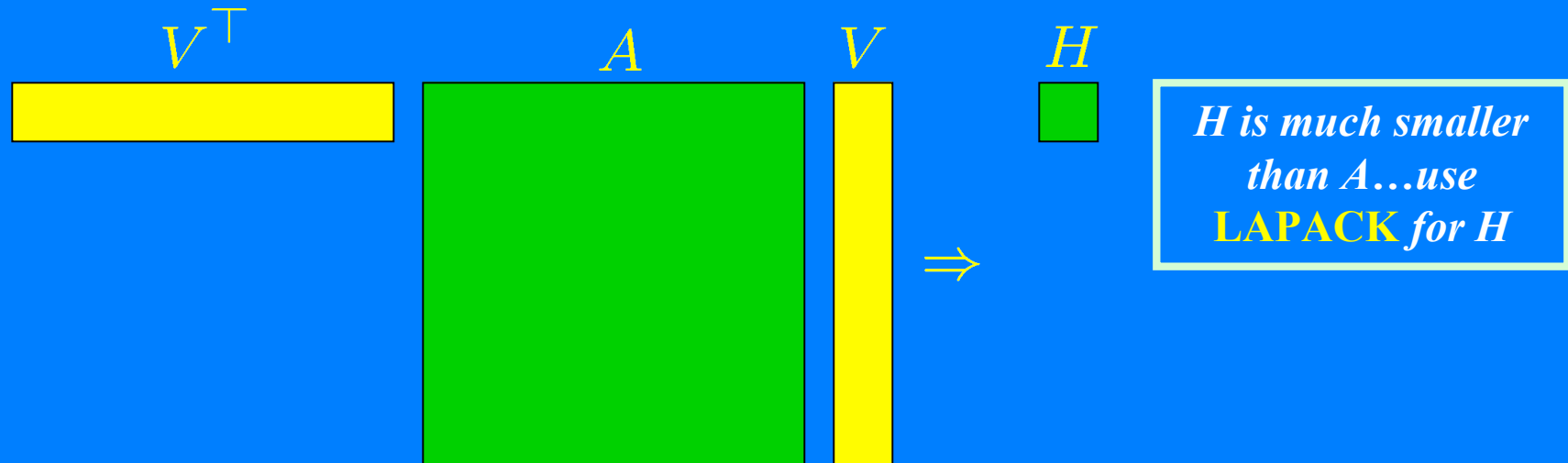
approximate the original problem with: $V^T AV y = \theta V^T V y$

Observe that:

- *Selecting V to have orthogonal columns ... $V^T V = I$... but it is expensive to come up with an orthogonal V*
- *Set $H = V^T AV$... then H is $k \times k$...much smaller than $N \times N$*

$$Hy = \theta y, \quad \lambda \approx \theta, \quad x \approx Vy$$

Subspace Methods



How to compute orthogonal V ?

- For a non-symmetric matrix A ...use Gram-Schmidt (Arnoldi)...
- For a symmetric matrix A (our case) use Lanczos...
- Other approaches available (i.e. Jacobi-Davidson) but still some sort of Gram-Schmidt is required...

REMINDER

We need many eigenvalues/vectors $O(1000)$...thus V may not be that thin!!!

Symmetric Problems: Lanczos

Basic property

Theoretically...(assuming no round-off errors)...Lanczos can build a very large orthogonal basis V requiring in memory only 3 columns of V at each step!

Lanczos

1. Input: Matrix A , unit norm starting vector v_0 , $\beta_0 = 0$, # k
2. For $j = 1, 2, \dots, k$ Do

3. $w_j = Av_j$	MATRIX VECTOR	NO SYNC.
4. $w_j = w_j - \beta_j v_{j-1}$	DAXPY	NO SYNC.
5. $\alpha_j = (w_j, v_j)$	DOT PRODUCT	SYNC. -BCAST
6. $w_j = w_j - \alpha_j v_j$	DAXPY	NO SYNC.
7. $\beta_{j+1} = \ w_j\ _2$	DOT PRODUCT	SYNC. -BCAST
8. If $\beta_{j+1} = 0$ then STOP		
9. $v_{j+1} = w_j / \beta_{j+1}$	DSCAL	NO SYNC.
10. EndDO

Lanczos in Finite Arithmetic...

Round-off errors

- *Lanczos vectors v_i quickly loose orthogonality...so that*
- *$V^T V$ is no longer orthogonal...thus*
- *We need to check if v_j is \perp to previous vectors $0,1,\dots,j-1$*
- *If NOT ... reorthogonalize it against previous vectors (Gramm-Schmidt)*

Lanczos

1. Input: Matrix A , unit norm starting vector v_0 , $\beta_0 = 0$, # k
2. For $j = 1, 2, \dots, k$ Do
 3. $w_j = Av_j$
 4. $w_j = w_j - \beta_j v_{j-1}$
 5. $\alpha_j = (w_j, v_j)$
 6. $w_j = w_j - \alpha_j v_j$
 7. $\beta_{j+1} = \|w_j\|_2$
 8. If $\beta_{j+1} = 0$ then STOP
 9. $v_{j+1} = w_j / \beta_{j+1}$
10. EndDO

**ORTHOGONALITY IS LOST
HERE...SO THESE STEPS ARE
REPEATED AGAINST *ALL*
PREVIOUS VECTORS...
SELECTIVE REORTH IS ALSO
POSSIBLE (SIMON, LARSEN)**

Practical Eigensolvers and Limitations

ARPACK (Sorensen-Lehoucq-Yang): Restarted Lanczos

- *Remember that $O(1000)$ eigenvalues/vectors are required...thus*
- *we need a very long basis $V...k = \text{twice the number of eigenvalues which}$*
- *will result in a large number of reorthogonalizations...*
- *Synchronization costs – Reorthogonalization costs – and Memory costs become intractable for large problems of interest...*

Shift-Invert Lanczos (Grimes et al) – Rational Krylov (Ruhe)

- *work with matrix $(A - \sigma_i I)^{-1}$ instead...*
- *compute some of the eigenvalues close to σ_i each time...thus a smaller basis is required each time...BUT*
- *many shifts σ_i are required...*
- *cost of working with the different “inverses” $(A - \sigma_i I)^{-1}$ becomes prohibitive for (practically) large Hamiltonians...*

We need alternative methods that can build large projection bases without the reorthogonalization-synchronization costs

Automated Multilevel Substructuring

Component Mode Synthesis (CMS) (Hurty '60, Graig-Bampton '68)

Well known alternative to Lanczos type methods. Used for many years in Structural Engineering. *But it too suffers from limitations due to problem size...*

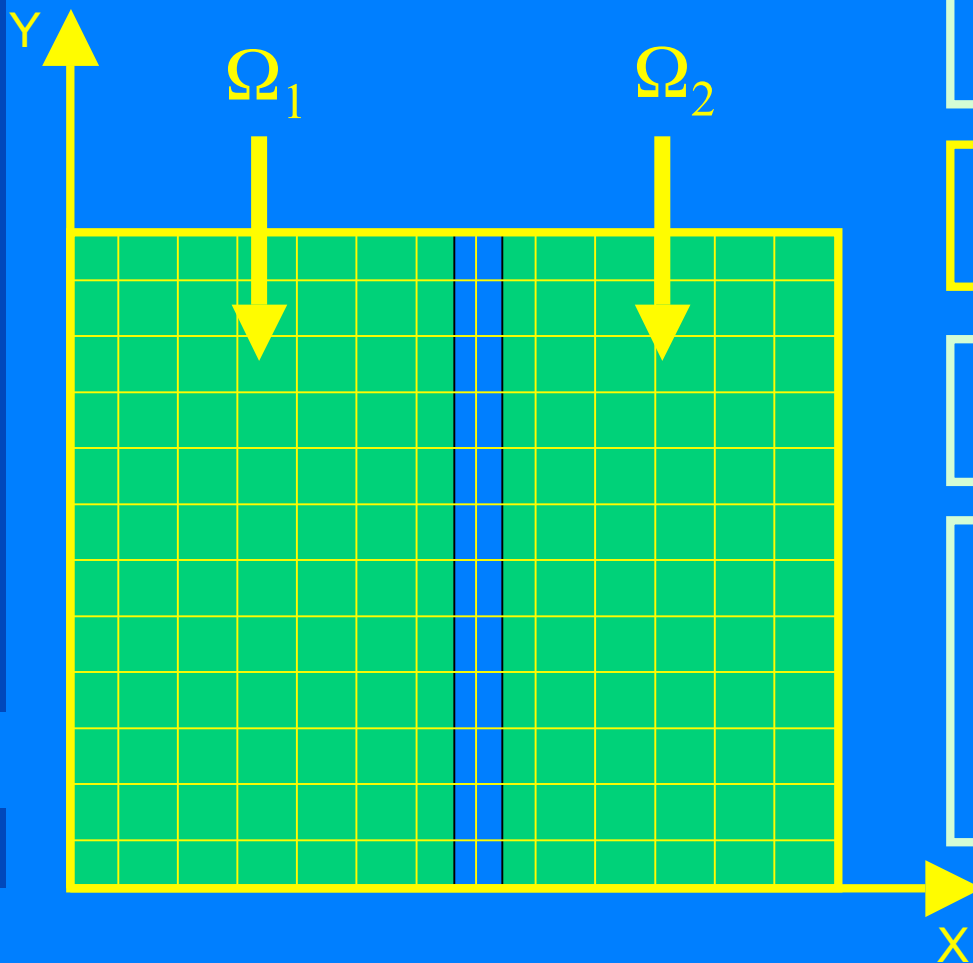
AMLS, (Bennighof, Lehoucq, Kaplan and collaborators)

- Multilevel CMS method (solves the dimensionality problem)
- Automatic computation of substructures (easy application)
- Approximation: Truncated Congruence Transformation
- Builds very large projection basis without reorthogonalization
- Successful in computing thousands of eigenvalues in vibro-acoustic analysis ($N > 10^7$) in a few hours on workstations (Kropp–Heiserer, 02)

Spectral Schur Complements (Bekas, Saad)

- ✓ Significantly improves AMLS accuracy...suitable for electronic structure calculations
- ✓ (unlike AMLS) ...framework for the iterative refinement of the approximations

Component Mode Synthesis: a model problem



Consider the model problem:

$$-\nabla^2 u = \lambda u$$

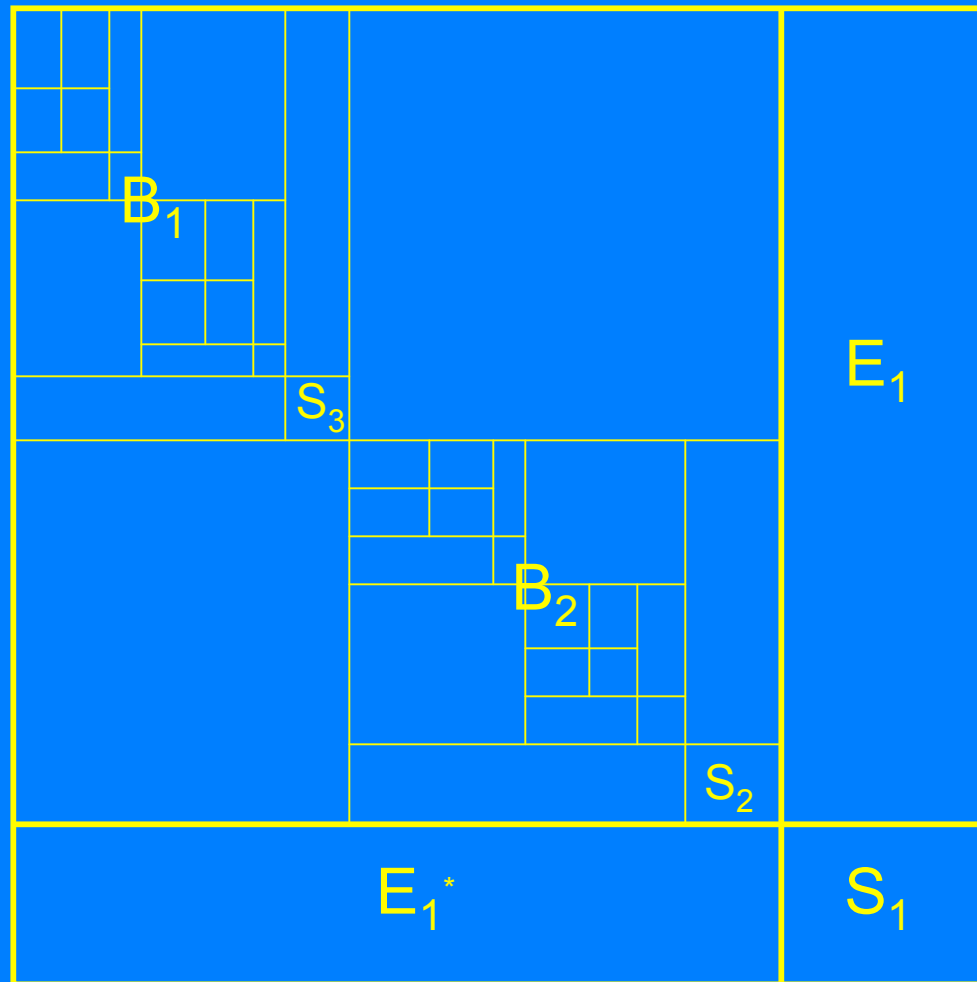
on the unit square Ω . We wish to compute smallest eigenvalues.

Subdivide Ω into 2 subdomains: Ω_1 and Ω_2

Component Mode Synthesis

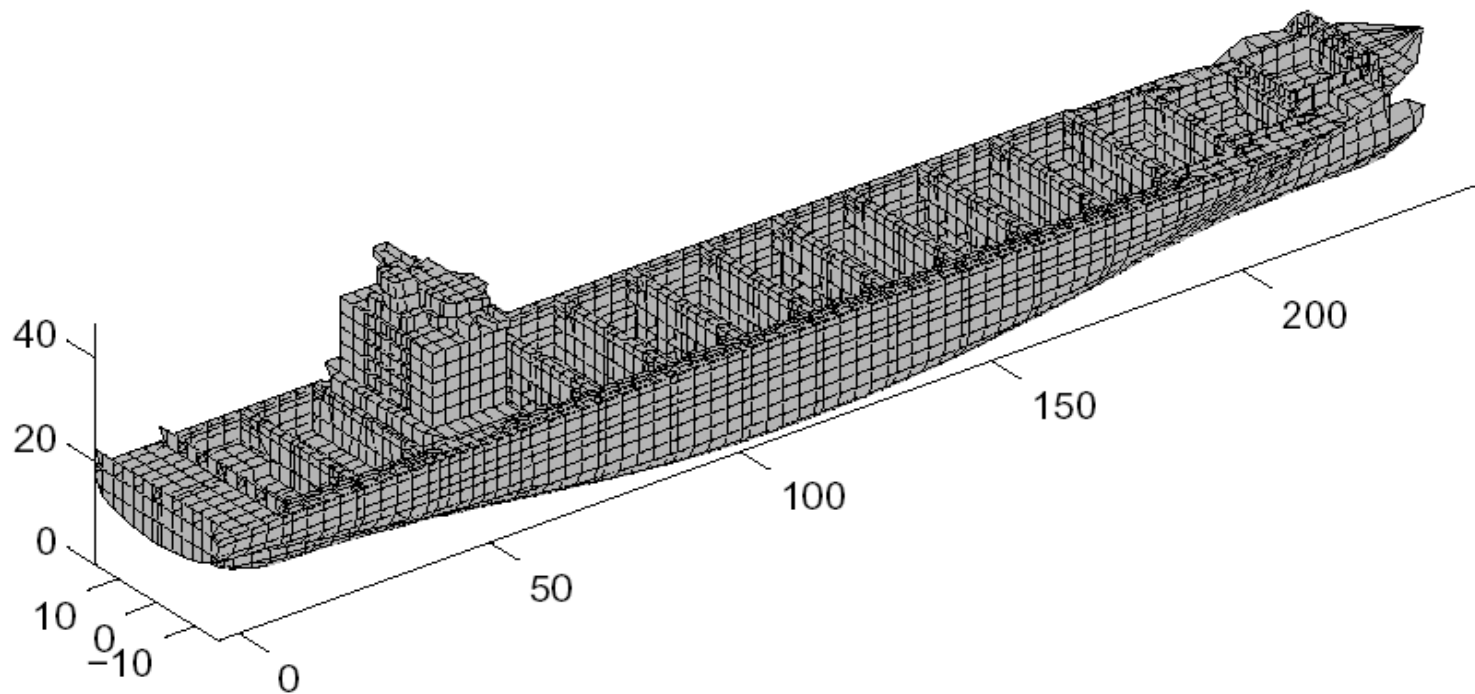
- Solve problem on each Ω_i
- “Combine” partial solutions

AMLS: Multilevel application



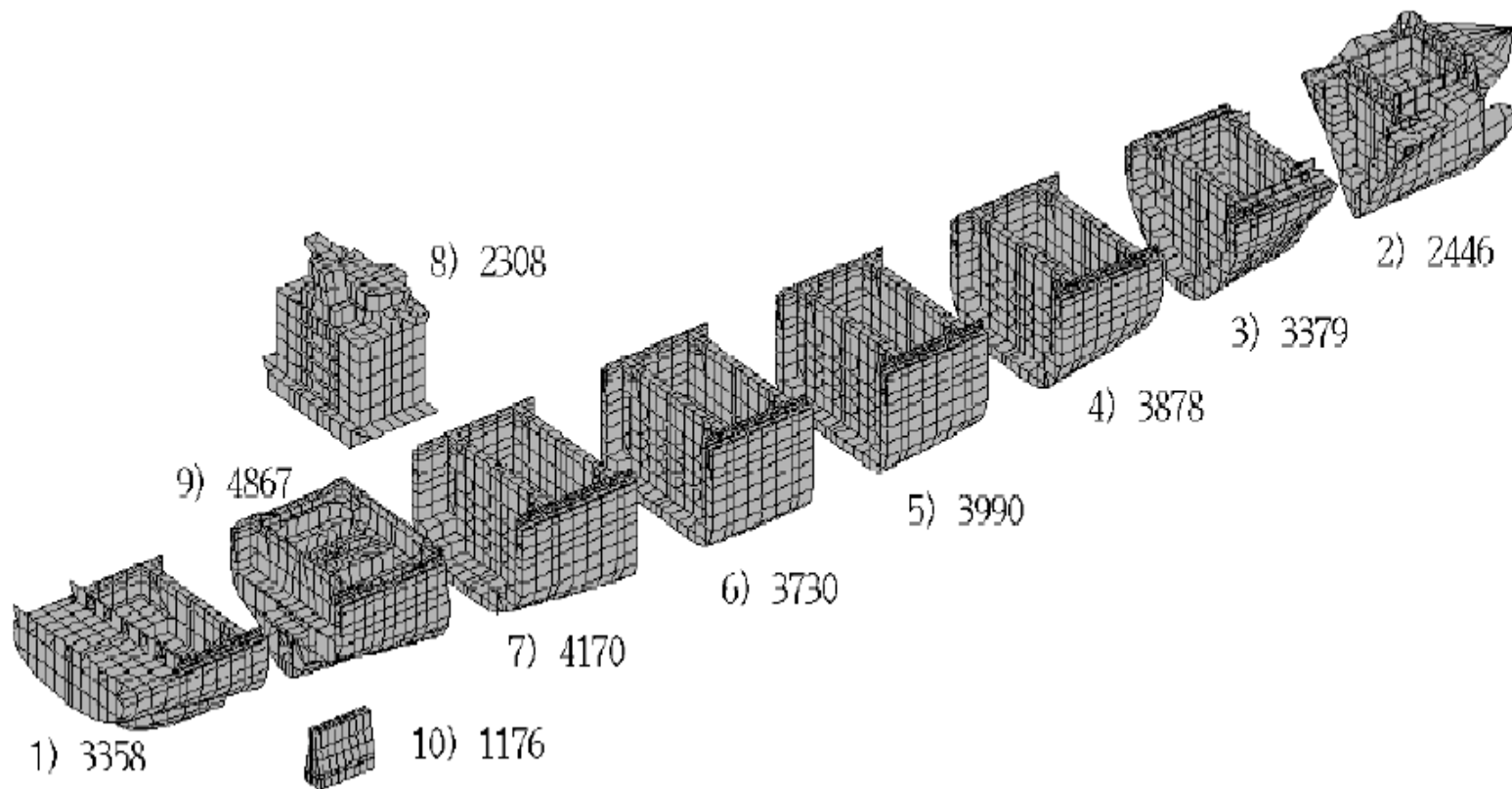
Scheme applied recursively. Resulting to thousands of subdomains. Successful in computing thousands smallest eigenvalues in vibro-acoustic analysis with problem size $N > 10^7$ (Kropp – Heiserer BMW)

AMLS: Example



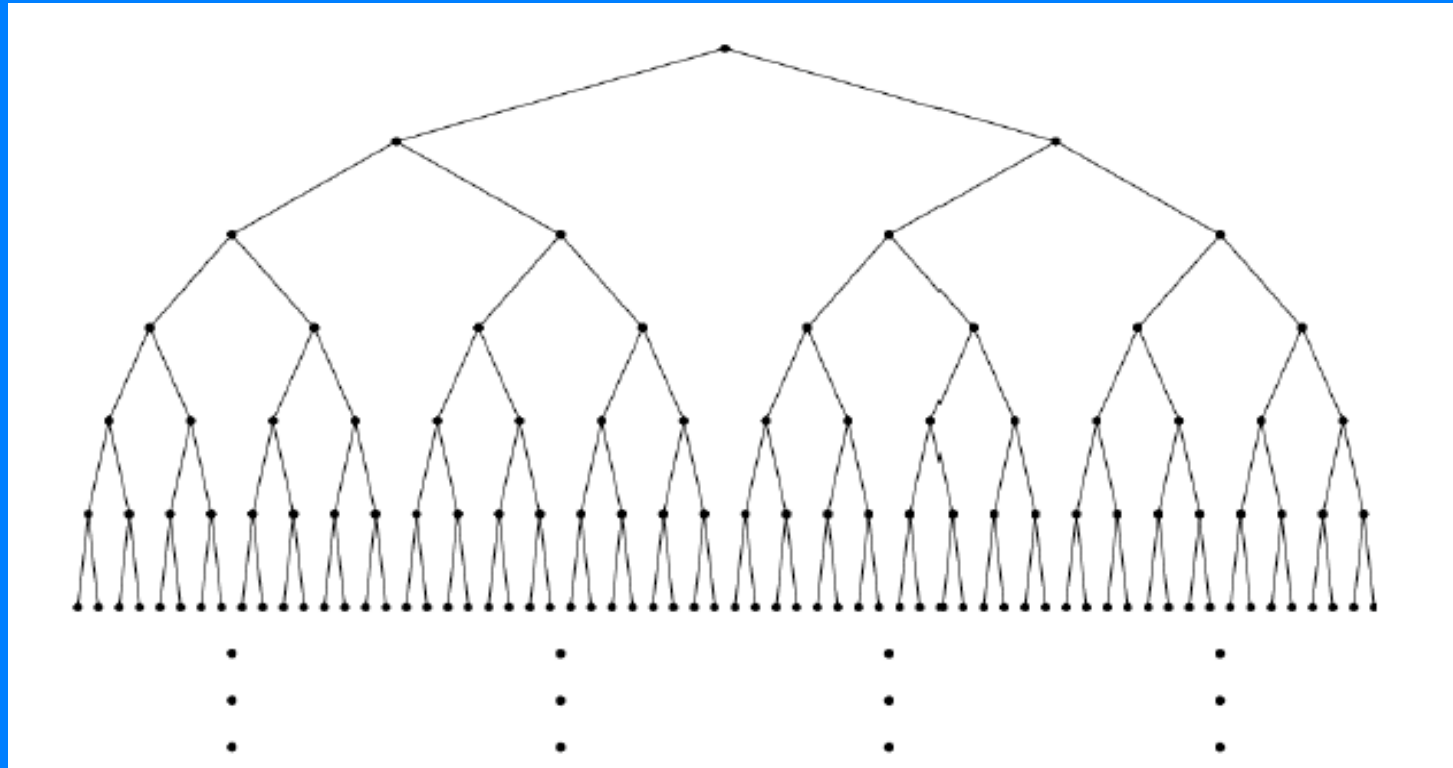
**Example: Container ship, 35K degrees of freedom
(Research group of prof. H. Voss, T. U. Hamburg, Germany)**

AMLS: Example



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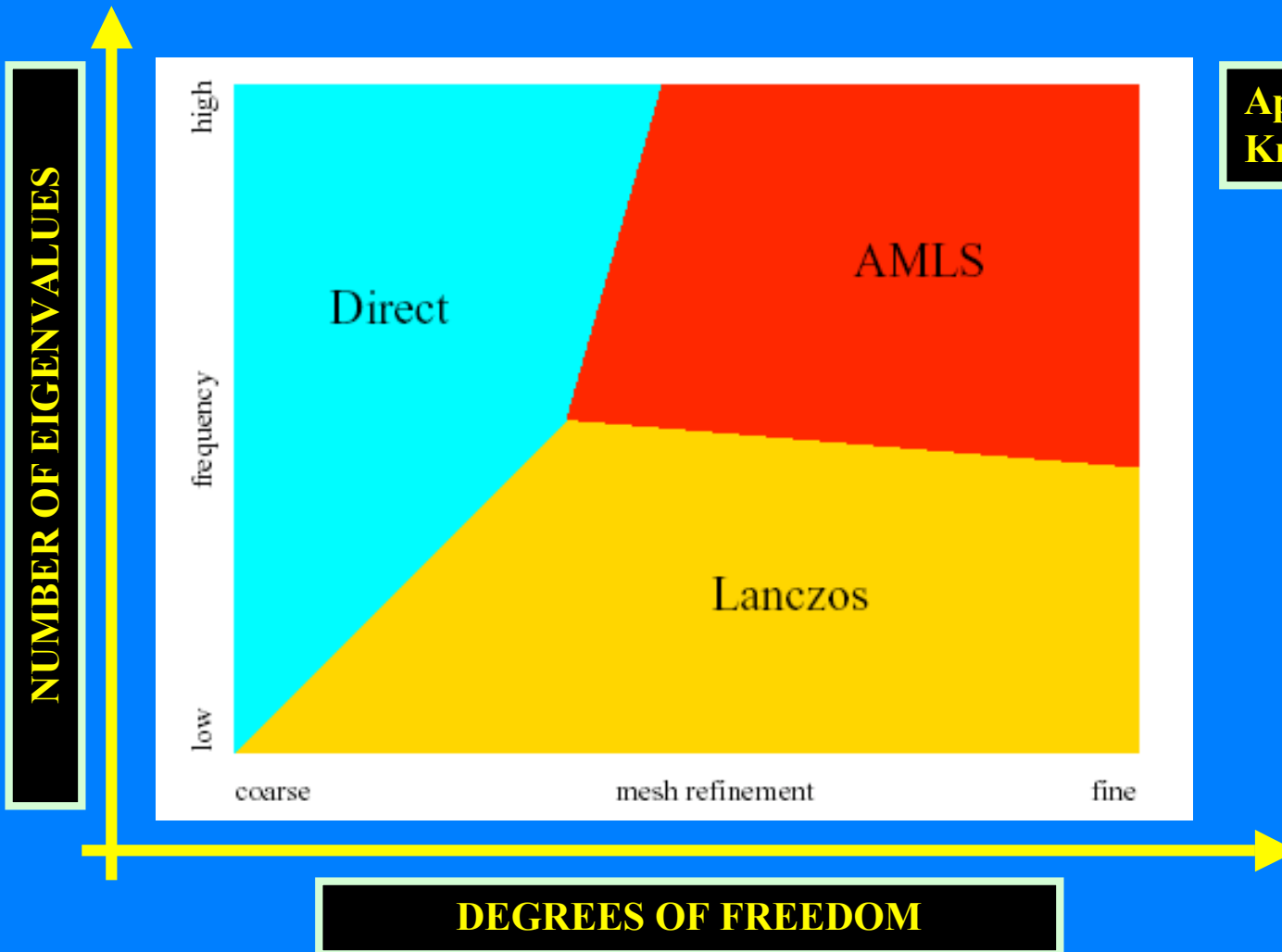
AMLS: Example



AMLS: Substructure tree (Kropp-Heiserer, BMW)

- Multilevel parallelism...
- Both Top-Down and Bottom-Up implementations are possible...
- At each node we need to solve a linear system...
- Multilevel solution of linear systems...level k depends-benefits from level $k+1$

Problem Set...AMLS v.s. Standard Methods



Application Domains,
Kropp-Heiserer, 02

Implementation Issues – Trilinos

ab initio calculations:...many ingredients required for successful techniques

- Mesh generation...discretization
- Visualization of input data...results...geometry
- Efficient data structures-communicators for parallel computations
- Efficient (parallel) Matrix-Vector and inner products
- Linear system solvers
- State-of-the-art eigensolvers...

A unifying software development environment will prove to be very useful

- ease of use...
- reusability...(object oriented)
- portable...

TRILINOS <http://software.sandia.gov/trilinos>

- software multi-package...developed at SANDIA (M. Heroux)
- modular...no need to install everything in order to work!
- Capabilities of LAPACK, AZTEC, Chaco, SuperLU, etc...combined
- very active user community...ever evolving!
- ease of use...without sacrificing performance

Conclusions

Large Scale Challenges in Computational Materials Science

- In DFT eigenvalue calculations dominate...
- ...many $O(1000)$ eigenvalues/vectors required...
- ...easily reaching and exceeding the limits of state-of-the-art traditional solvers
- AMLS appears as an extremely attractive alternative...however accuracy requirements and efficient parallel implementation is still under development

Many open problems in *ab initio* calculations...one of the most active fields of research today!