

Parallel research of numerous eigenvalues in ABINIT

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Framework of the problem

- Calculation of the ground-state energy $E^{KS}(\rho)$, for a fixed geometry.

$$\begin{cases} \bar{H}\varphi_i = \varepsilon_i\varphi_i, \quad \forall i = 1, \dots, N, \\ \int_{\mathbb{R}^3} \varphi_i\varphi_j^* = \delta_{ij}. \end{cases}$$

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- Numerical resolution: discretization in a finite dimension basis $\{\chi_j\}_{j=1, \dots, M}$ (Galerkin method)
 \Rightarrow generalized eigenvalue problem

$$\varphi_i = \sum_{j=1}^M c_{ji}\chi_j \Rightarrow \tilde{H}\mathbf{c}_i = \varepsilon_i S\mathbf{c}_i, \quad \forall i = 1, \dots, N$$

\tilde{H} : discretized KS Hamiltonian; S : overlap matrix

Numerical resolution

- Direct minimization of $E^{KS}(\rho)$, by nonlinear conjugate gradient (NLCG) algorithm

$$\min \left\{ \sum_{i=1}^N (\tilde{H}\psi_i, \psi_i); (\psi_i, \psi_j) = \delta_{ij} \right\}$$

$\{\psi_i\}$: wave vectors; $\{\varphi_i\}$: KS orbitals

At SCF convergence:

$$\text{Span}(\psi_1, \dots, \psi_N) = \text{Span}(\varphi_1, \dots, \varphi_N)$$

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- Complexity (orthogonalization of the ψ_i): $\mathcal{O}(MN^2)$ or $\mathcal{O}(N^3)$. (matrix/vectors products in $\mathcal{O}(N^2 \log N)$)

Specificities of the ABINIT code and difficulties:

- for each SCF loop, calculation of pseudo-eigenvectors (i.e. not converged)
- \tilde{H} : full symmetric matrix, of very large dimension and not explicitly known
- the eigenvalues calculation is intrinsically not parallel

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Goal: propose parallel methods to realize calculations on more complex molecular systems.

New algorithm (1)

- **calculation of exact eigenvectors** instead of pseudo-eigenvectors \Rightarrow orthogonality of the ψ_i (\tilde{H} symmetric) such that

$$\min \left\{ \sum_{i=1}^N ((\tilde{H} - \lambda_i I)^2 \psi_i, \psi_i) \right\}$$

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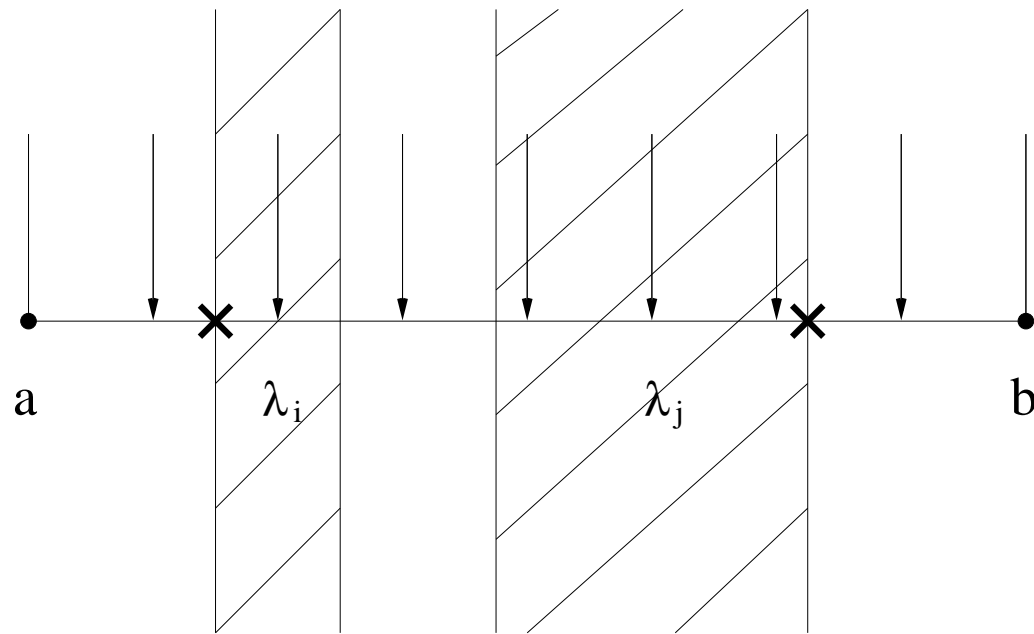
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Proposals for the choice of a and b :

- given by the code user
- Lanczos algorithm
- estimate of the N^{th} eigenvalue of \bar{H}

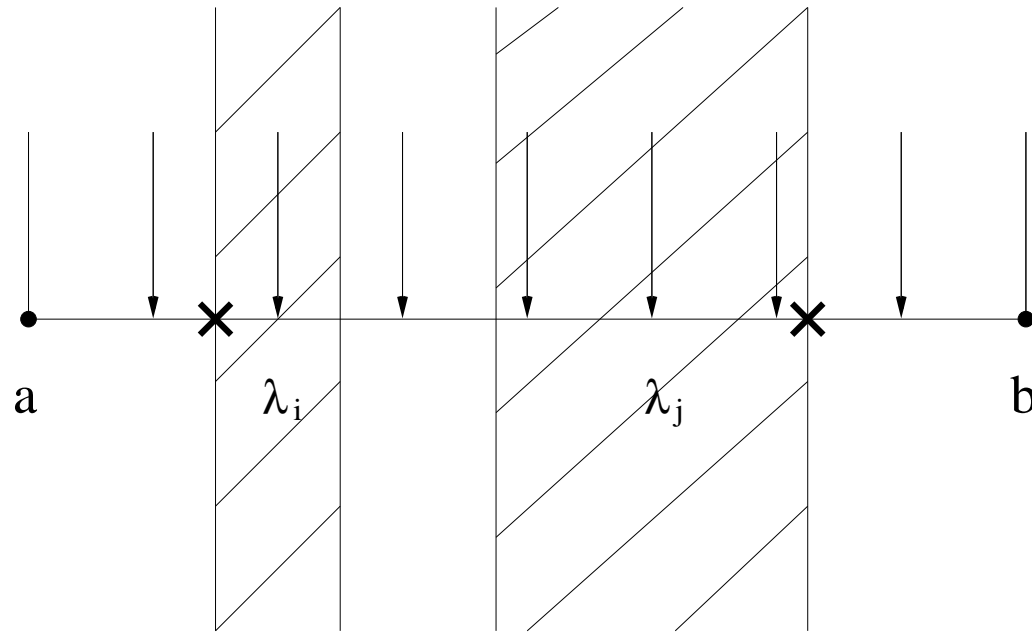
Spectral partitioning: details

- Iterative algorithm with dynamic allocations of shifts λ_i until $[a, b]$ is completely explored.



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- $k > N$ eigenvalues in $[a, b] \Rightarrow \alpha k$ research of eigenvalues ($3 < \alpha < 4$).

- To take into account of multiple eigenvalues:

$$\min \left\{ \sum_{i=1}^{N_n} \sum_{j=1}^n \left((\tilde{H} - \lambda_i I)^2 \psi_{ij}, \psi_{ij} \right), (\psi_{ij}, \psi_{ik}) = \delta_{jk} \right\},$$

where $N_n = \frac{N}{n}$ is the number of blocks of n wave vectors ($n \in \{1, 2, 3, 4\}$).

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- Theoretical complexity: $N_n \times Mn^2 = nMN \Rightarrow \mathcal{O}(N^2)$ sequentially.

Results and conclusions:

- Principle of the algorithm without reorthog. is validated (H_2, Si) but ... real complexity: $\alpha N^3 \rightarrow \beta N^2$ with $\beta \gg \alpha$ because:

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- calculation of exact eigenvalues by NLCG can be very hard. The difficulties are:

$$\left\{ \begin{array}{l} \cdot \text{numerical: } \text{cond}(\psi_k) = \frac{\lambda_{\max}}{\min_{j \neq k} |\lambda_j - \lambda_k|} \\ \cdot \text{physical: spectrum of Hamiltonians has not a regular distribution} \end{array} \right.$$

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- E^{KS} and ρ are invariant under any unitary transformation

\Rightarrow proposal of a new algorithm (2) with calculations of clusters of eigenvalues.

New algorithm (2)

- Calculation of eigensubspaces with local reorthog. by

$$\left\{ \begin{array}{l} \cdot \text{NLCG on } (\tilde{H} - \lambda_i I)^2 \\ \cdot \text{Lanczos on } (\tilde{H} - \lambda_i I)^{-1} \end{array} \right.$$

New algorithm (2)

- Calculation of eigensubspaces with local reorthog. by
 - NLCG on $(\tilde{H} - \lambda_i I)^2$
 - Lanczos on $(\tilde{H} - \lambda_i I)^{-1}$
- Hierarchy of algorithms:

Original ABINIT, full reorthog. $\mathcal{O}(N^3)$
 \Rightarrow SCF convergence



algo. (2), with partial reorthog.
 \Rightarrow convergence of eigenspaces



algo. (1), without reorthog. $\mathcal{O}\left(\frac{N^2}{N_{proc}}\right)$
 \Rightarrow bad convergence of eigenvectors

- Numerical property of NLCG for eigensubspaces calculation:

Proposition 1. *Let A be a matrix of order M and $\{u_j, \lambda_j\}$ its eigenstates such that $|\lambda_1 - \mu| < \dots < |\lambda_M - \mu|$. Then the convergence factor of the approximated eigenspace of dimension m is $\mathcal{O}\left(\left|\frac{\lambda_m - \mu}{\lambda_{m+1} - \mu}\right|\right)$ (subspace iteration algorithm).*

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- \Rightarrow if $m_\mu =$ dimension of the closest cluster near μ then:

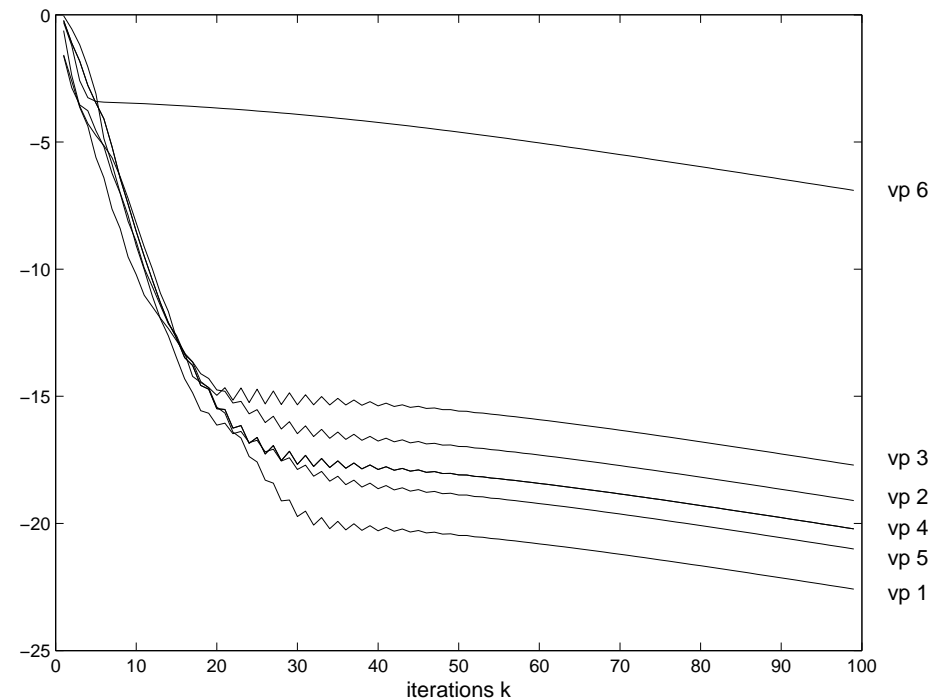
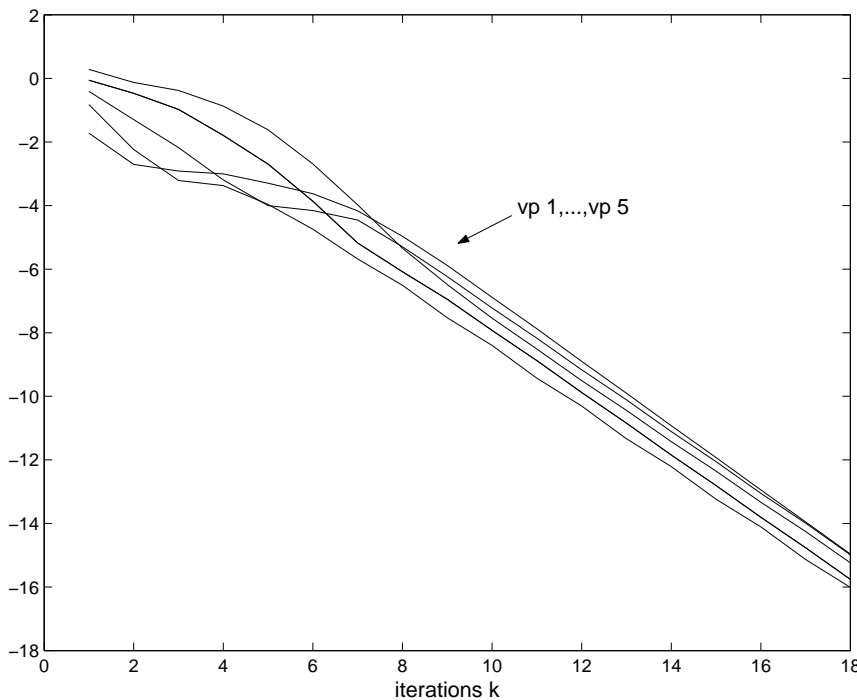
- $m < m_\mu$: very slow convergence
- $m = m_\mu$: optimal convergence
- $m > m_\mu$: it depends of the \exists of other clusters

- **Exemple:** A diagonal, $\dim(A) = 20$, concentrated spectrum:

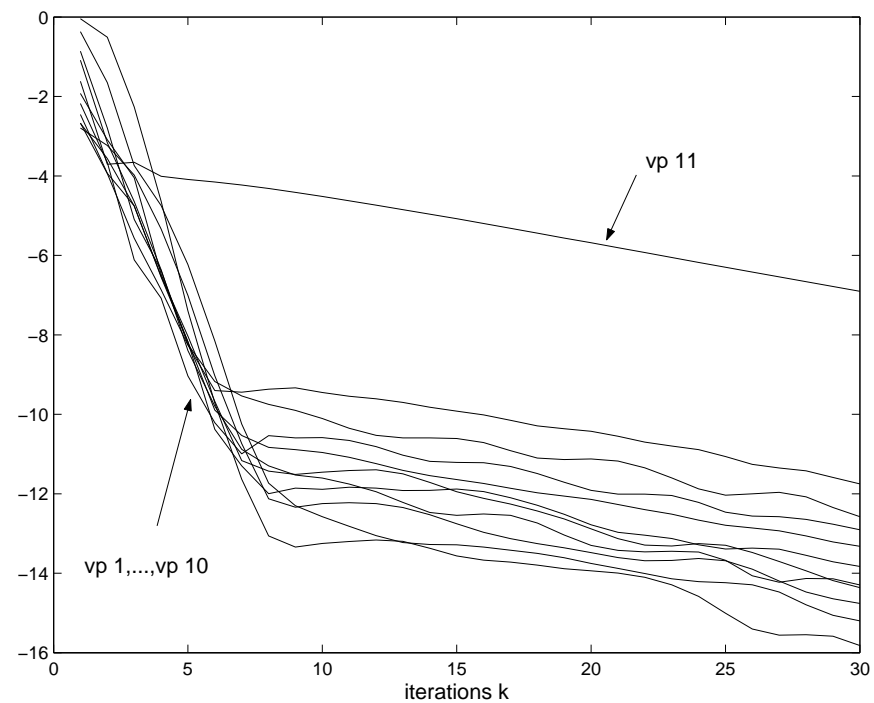
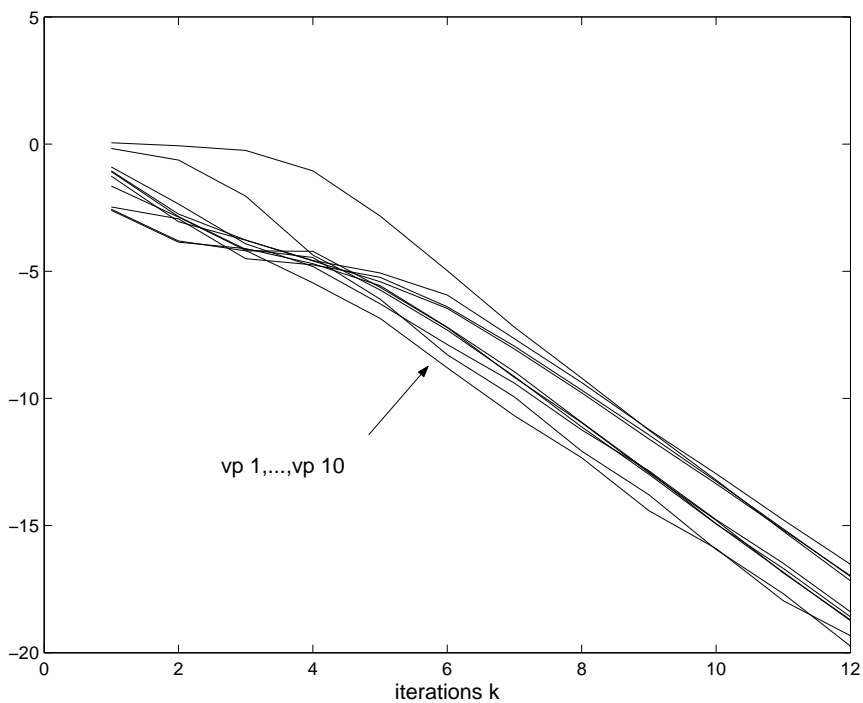
$$\text{sp}(A) = \{0.99, 1.02, 1.03, 1.04, 1.05, \dots, 3.99, 4.02, 4.03, 4.04, 4.05\}$$

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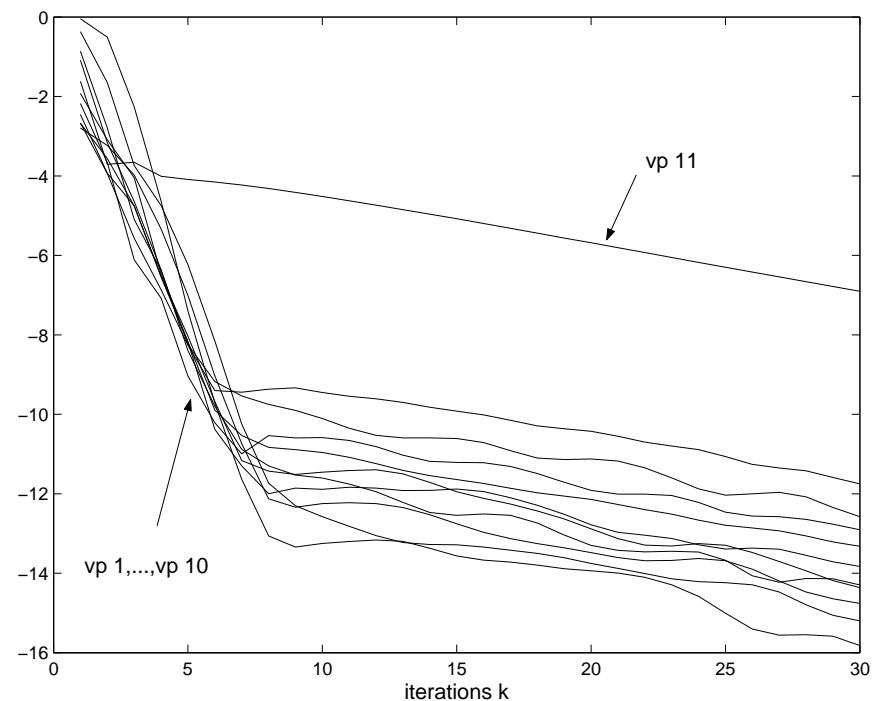
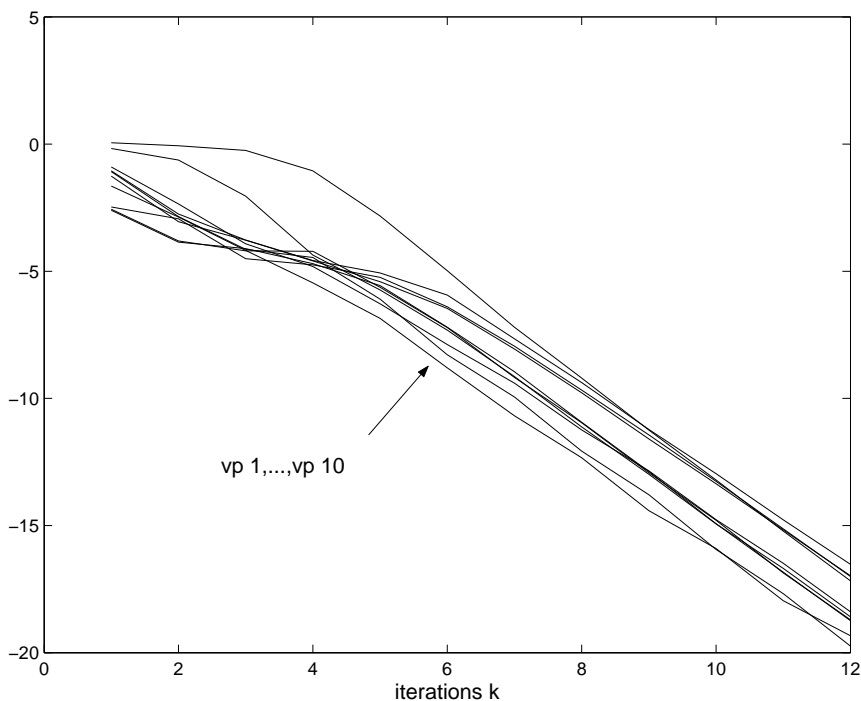
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$$\mu = -1.0, \log(|\lambda_i^{(k)} - \lambda_i|) = f(k), \quad m = 5 \text{ et } 6.$$



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\Rightarrow convergence of sub-clusters of eigenvalues gives another criterium of partitionning of $[a, b]$, related to physical properties.

● In a few words:

(1) - Spectral slice of an energy band with bounds to be chosen

(2) - Filling of energy regions via calculations of eigensubspaces, with local reorthog. Two ways:

$$\left\{ \begin{array}{l} (2.1) - \text{Lanczos on } (\tilde{H} - \lambda_i I)^{-1} \\ \Rightarrow \text{“Classical” partitionning.} \\ (2.2) - \text{NLCG on } (\tilde{H} - \lambda_i I)^2 \\ \Rightarrow \text{Physical partitionning related to the} \\ \text{clusters of eigenvalues.} \end{array} \right.$$

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- “Long distance orthogonality”: theorems quantifying the speed of orthog. between 2 vectors for different algorithms (numerical and theoretical studies).