

# Convergence of inexact adaptive finite element solvers

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EFEF, ACMAC, Ηράκλειο, 31.05 – 01.06.2013

# Overview

- 1 The setting
- 2 Inexact SOLVE – theory
- 3 Adaptive stopping criteria for CG
- 4 Numerical Experiments

 M. ARIOLI, E.H. GEORGOULIS , AND D. LOGHIN  
Stopping criteria for adaptive finite element solvers  
*SIAM J. Sci. Comput.*, to appear.

# The setting

Let  $\Omega \subset \mathbb{R}^d$ ,  $d = 2, 3$ . Consider

$$\begin{aligned} -\nabla \cdot (a \nabla u) &= f && \text{in } \Omega \\ u &= 0 && \text{on } \partial\Omega \end{aligned}$$

with  $a \in [L^\infty(\Omega)]^{d \times d}$  SPD, and  $f \in L^2(\Omega)$ .

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Finite element space  $\mathcal{V} := \{V \in H_0^1(\Omega) : V|_\kappa \circ F_\kappa \in \mathcal{P}_r(\hat{\kappa}), \kappa \in \mathcal{T}\}$ .

The finite element method reads:

$$\text{find } U \in \mathcal{V} \text{ such that } a(U, V) = l(V) \quad \forall V \in \mathcal{V}$$

where

$$a(w, v) := \int_{\Omega} a \nabla w \cdot \nabla v \, dx \quad \text{and} \quad l(v) := \int_{\Omega} f v \, dx$$

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**Question:** Guaranteed convergence of AFEM with inexactness in “SOLVE”?



# AFEM Convergence with exact SOLVE

SOLVE:

$$\text{find } U_m^e \in \mathcal{V}_m \text{ such that } a(U_m^e, V_m) = l(V_m) \quad \forall V_m \in \mathcal{V}_m.$$

ESTIMATE:

$$\eta_{\mathcal{T}_m}^2(U_m^e, \kappa) := h_\kappa^2 \|f + \nabla \cdot (a \nabla U_m^e)\|_\kappa^2 + \sum_{e \in \Gamma_{\text{int}, m} \cap \partial \kappa} h_e \|[a \nabla U_m^e \cdot \mathbf{n}]\|_e^2.$$

MARK:

For some  $0 < \theta \leq 1$ , find  $\mathcal{M}_m \subset \mathcal{T}_m$ :

$$\eta_{\mathcal{T}_m}^2(U_m^e, \mathcal{M}_m) \geq \theta \eta_{\mathcal{T}_m}^2(U_m^e, \mathcal{T}_m).$$

REFINE:

Standard mesh refinement (newest vertex bisection)

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Theorem (Cascon, Kreuzer, Nochetto & Siebert '08)

There exist constants  $\xi > 0$  and  $0 < \alpha < 1$  such that

$$\|u - U_{m+1}^e\|_a^2 + \xi \eta_{\mathcal{T}_{m+1}}^2(U_{m+1}^e, \mathcal{T}_{m+1}) \leq \alpha (\|u - U_m^e\|_a^2 + \xi \eta_{\mathcal{T}_m}^2(U_m^e, \mathcal{T}_m)).$$

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with inexact solution satisfying a given criterion.

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} with  $U_m$  if exact and with  $\tilde{U}_m$  if inexact.

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**Remark:** In general, we arrive to different meshes for each case.

# AFEM Convergence with **inexact** SOLVE

## Theorem

Let  $u$ ,  $\theta$ ,  $\tilde{U}_m$  and  $\tilde{U}_{m+1}$ ,  $m \geq 1$  as above, be such that

$$\mu_1 \|\tilde{U}_m - U_m\|_a^2 + \mu_2 \|\tilde{U}_{m+1} - U_{m+1}\|_a^2 \leq \nu_1 \eta_m^2(\tilde{U}_m) + \nu_2 \eta_{m+1}^2(\tilde{U}_{m+1}),$$

for suitably chosen  $\mu_1, \mu_2 > 0$  and  $\nu_1, \nu_2 \geq 0$ . Then, there exist a constant  $0 < \alpha < 1$ , depending only on the shape regularity of  $\tilde{T}_1$  and on the marking parameter  $\theta$ , such that

$$\|u - \tilde{U}_{m+1}\|_a^2 + \zeta \eta_{m+1}^2(\tilde{U}_{m+1}) \leq \alpha (\|u - \tilde{U}_m\|_a^2 + \zeta \eta_m^2(\tilde{U}_m)),$$

for some  $\zeta \equiv \zeta(\mu_1, \mu_2, \nu_1, \nu_2) > 0$ .

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Extends known results.



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## Corollary

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for suitably chosen  $\mu > 0$  and  $\nu > 0$ . Then, there exist a constant  $0 < \alpha < 1$ , depending only on the shape regularity of  $\tilde{T}_1$  and on the marking parameter  $\theta$ , such that

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**Remark:** We estimate inexactness using information from previous iteration only!

## Stopping criteria for linear solvers

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Focus on iterative linear solvers: [Conjugate Gradient](#)

# Stopping criteria for linear solvers

Linear system

$$A_m \mathbf{u}_m = \mathbf{b}_m$$

and let  $\mathbf{u}_m^k$  the  $k$ -th CG iterate at **step  $m$**  of AFEM corresponding to  $U_m^k \in \tilde{\mathcal{V}}_m$ .

Then:

$$\|U_m - U_m^k\|_a = \|\mathbf{u}_m - \mathbf{u}_m^k\|_{A_m} = \|\mathbf{r}_m^k\|_{A_m^{-1}}, \quad \mathbf{r}_m^k := \mathbf{b}_m - A_m \mathbf{u}_m^k$$

where  $\langle x, y \rangle_A := x^T A y$ ,  $x, y \in \mathbb{R}^N$ ,

## Estimation of the residual – Golub-Meurant bound

Recalling that for CG, we have  $(\mathbf{r}_m^k)^T \mathbf{u}_m^k = 0$ , then

$$\|\mathbf{u}_m - \mathbf{u}_m^k\|_{A_m}^2 = \|\mathbf{r}_m^k\|_{A_m^{-1}}^2 = \mathbf{b}_m^T A_m^{-1} \mathbf{b}_m - \mathbf{b}_m^T \mathbf{u}_m^k.$$



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Crucially, we can have

$$F(A_m) = \mathbf{b}_m^T A_m^{-1} \mathbf{b}_m = \int_{\lambda_{\min}(A_m)}^{\lambda_{\max}(A_m)} \lambda^{-1} d\omega(\lambda),$$

where the measure  $\omega$  is a non-decreasing step function with jump discontinuities depending on the Fourier coefficients of  $\mathbf{b}_m$  at the eigenvalues of  $A_m$ .

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**Challenge:** Find guaranteed lower bound  $\lambda < \lambda_{\min}(A_m)$ .

## Lower bounds for $\lambda_{\min}(A_m)$

- Poincaré inequality  $\|v\|_{L^2(\Omega)} \leq C_P |v|_{H^1(\Omega)} +$  (Wathen '87)  $\longrightarrow$

$$\lambda_{\min}(A_m) \geq \frac{a_{\min}}{C_P^2} \min_{\kappa \in \mathcal{T}_m} \lambda_{\min}(M_\kappa)$$

where  $M_\kappa$  elemental mass matrices.

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- We can use “adaptive” Poincaré estimate:

### Lemma (Loghin '13?)

Let  $\mathcal{D}_m \supseteq \tilde{\mathcal{M}}_m$  region of refined elements, s.t.  $\partial\Omega \neq \mathcal{D}_m \cap \partial\Omega \neq \emptyset$ . Let  $A_m, A_{m+1}$  denote the matrices assembled on consecutive subdivisions in the inexact AFEM algorithm. Then

$$\lambda_{\min}(A_{m+1}) \geq \min \left\{ \lambda_{\min}(A_m), \frac{a_{\min}}{(C_P^m)^2} \min_{\kappa \in \mathcal{D}_m} \lambda_{\min}(M_\kappa) \right\}.$$

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- Estimates using Lanczos algorithm

# Numerical Experiments

- 1 DNR: ideal bound using the exact dual norm of the residual;
  - 2 GM0: ideal Golub-Meurant upper bound using the exact  $\lambda_{\min}(A_m)$ ;
- 
- 3 GM1: Golub-Meurant upper bound with adaptive bounds for  $\lambda_{\min}(A_m)$ ;
  - 4 GM2: Golub-Meurant upper bound with global Poincaré bound for  $\lambda_{\min}(A_m)$ ;
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- 5 GM3: Golub-Meurant with Lanczos estimate for  $\lambda_{\min}(A_m)$ ;
  - 6 HS: the Hestenes-Stiefel estimator (delay  $d = 5$  steps);
  - 7 AG: the anti-Gauss estimator;
  - 8 ER( $|\log tol|$ ): the standard Euclidean residual with various stopping tolerances  $tol$ .



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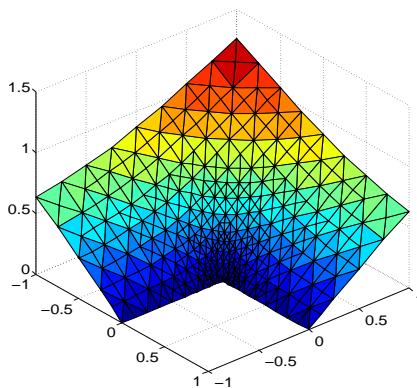
CG iteration has a cost proportional to the number of nonzeros, the cost formula employed is

$$mv := \text{matvecs}(m) = \sum_{k=1}^m \frac{\text{nnz}(A_k)}{\text{nnz}(A_m)} \cdot \text{its}(k),$$

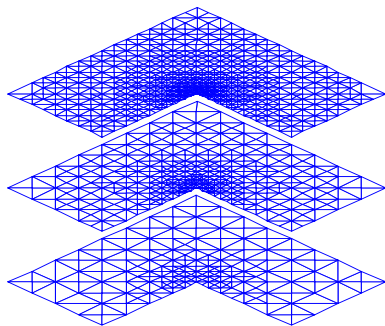
where  $\text{nnz}(A_k)$  number of nonzero elements of  $A_k$

# Test problem 1

$$\theta = 0.75$$



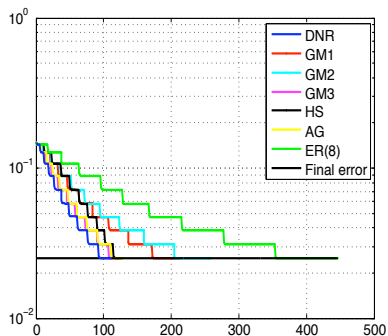
(a) Solution of test problem 1



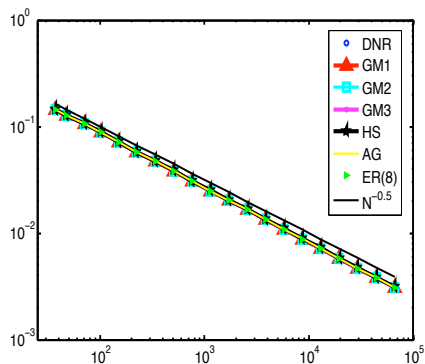
(b) Adaptive meshes:  $m = 4, 6, 8$ ;  $N_0 = 83$ .

Figure: Solution and adaptive meshes for Test problem 1

# Test problem 1



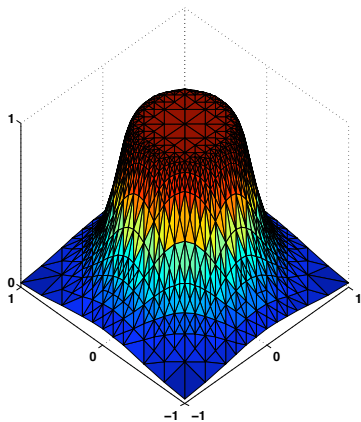
(a) Errors  $\|u - U_m^k\|_a$  for  $m = 10$ .



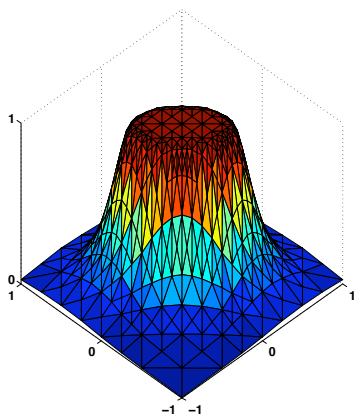
(b) Convergence rates, inexact AFEM,  $m = 20$ .

## Test problem 2

$$a = \frac{1}{\epsilon} \begin{pmatrix} 1 & \epsilon - 1 \\ \epsilon - 1 & 1 \end{pmatrix}$$

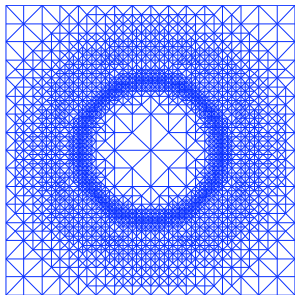


(c)  $\epsilon = 1$ .

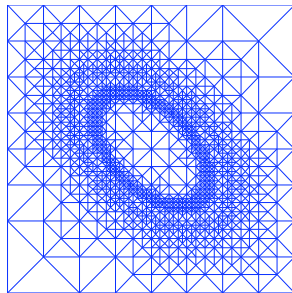


(d)  $\epsilon = 1/2$ .

## Test problem 2



(e)  $\epsilon = 1$ .



(f)  $\epsilon = 1/2$ .

Figure: Solutions and adaptive meshes ( $m = 10$ ) for Test problem 2

# Test problem 2 ( $m = 20$ )

method	$\epsilon = 1$			$\epsilon = 1/2$		
	$N_m$	$\ u - \tilde{U}_m\ _a$	mv	$N_m$	$\ u - \tilde{U}_m\ _a$	mv
exact	549,047	7.1750e-3	–	264,033	2.3346e-2	–
DNR	546,902	7.2040e-3	415	264,301	2.3416e-2	396
GM1	545,386	7.2009e-3	478	263,867	2.3359e-2	494
GM2	549,035	7.1750e-3	796	264,121	2.3343e-2	1,104
GM3	544,814	8.9772e-3	205	264,261	2.9244e-2	292
HS	539,606	1.4612e-2	11	264,814	1.1781e-1	13
AG	548,663	8.2482e-3	13	260,995	4.3329e-2	15
ER(6)	548,540	7.1782e-3	1,639	264,033	2.3346e-2	1,754
ER(8)	549,047	7.1750e-3	2,075	264,033	2.3346e-2	2,356
ER(10)	549,047	7.1750e-3	3,003	264,033	2.3346e-2	3,007

## Test problem 3

$$a = 1, u = \exp(-10r)$$

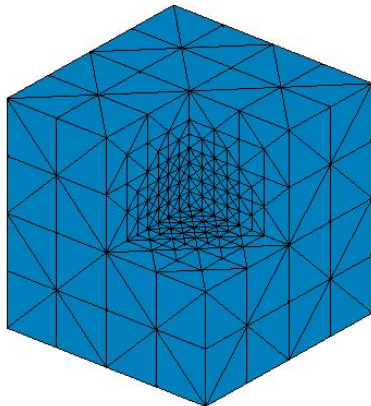


Figure: Adaptive meshing for test problem 3

# Test problem 3

method	$N_0 = 142$			$N_0 = 779$			$N_0 = 5,191$		
	$N_m$	$\ u - \tilde{U}_m\ _a$	mv	$N_m$	$\ u - \tilde{U}_m\ _a$	mv	$N_m$	$\ u - \tilde{U}_m\ _a$	mv
exact	19,579	8.9670e-2	-	131,250	4.7497e-2	-	950,961	†	-
DNR	19,507	8.9617e-2	120	131,452	4.7744e-2	302	†	†	†
GM1	19,573	8.9665e-2	179	131,243	4.7498e-2	447	951,057	2.4695e-2	1,065
GM2	19,582	8.9672e-2	250	131,232	4.7497e-2	570	950,988	2.4696e-2	1,292
GM3	19,510	8.9682e-2	151	131,251	4.7484e-2	353	951,077	2.4695e-2	1,018
HS	19,648	9.0596e-2	120	131,606	4.9477e-2	291	958,982	2.6542e-2	676
AG	*	*	*	*	*	*	*	*	*
ER(6)	19,587	8.9677e-2	238	131,246	4.7497e-2	465	951,239	2.4692e-2	958
ER(8)	19,579	8.9670e-2	331	131,250	4.7497e-2	649	950,954	2.4697e-2	1,505
ER(10)	19,579	8.9670e-2	412	131,250	4.7497e-2	840	950,932	2.4697e-2	2,001

Table:  $m=10$ . Legend: †: out of memory; -: does not apply; \*: does not exist.