



# A QMR method based on an A-biorthogonalization process

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CREST/COE Workshop  
October 25th, 2006  
The University of Tokyo

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# Table of Contents

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- Background / Motivation
  - Numerical methods for solving linear systems  
(The Krylov subspace methods)
- Theory
  - Bi-CG and QMR
  - Bi-CR and **Our method**
- Numerical experiments
- Summary and future plan



# Numerical methods for solving linear systems

$$Ax = b$$



## The Krylov subspace method

$$A = A^T$$

CG      CR

MINRES

$$A \neq A^T$$

Bi-CG

Bi-CR

QMR

GMRES



# The Krylov subspace method

$$Ax = b$$

Krylov subspace:  $K_n(A; \mathbf{r}_0) = \text{span}(\mathbf{r}_0, A\mathbf{r}_0, \dots, A^{n-1}\mathbf{r}_0)$



1. Generate basis vectors,  $V_n = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n]$

$V_n \longrightarrow$  Basis algorithm  
(Lanczos process, Arnoldi process...)

2. Get approximate solution,  $\mathbf{x}_n = \mathbf{x}_0 + V_n \mathbf{y}_n$ ,  $\mathbf{y}_n \in \mathbf{R}^n$

$\mathbf{y}_n \longrightarrow$  Residual condition  
(Orthogonal condition, Norm minimal condition...)



# Motivation



Smooth

Residual Basis	Orthogonal condition	QMR property
Bi-Lanczos process	Bi-CG	QMR
$A$ -biortho- gonalization process	Bi-CR	Our method



Fast



# Bi-CG and QMR

Basis algorithm: Bi-Lanczos process

- generates the basis vectors  $\{v_1^L, \dots, v_n^L\}$ ,  $\{w_1^L, \dots, w_n^L\}$  of two Krylov subspace,  $K_n(A; r_0)$ ,  $K_n(A^T; r_0^*)$
- Bi-orthogonality:  $(w_i^L, v_j^L) = \delta_{ij}$
- Matrix form:

$$\begin{aligned} AV_n^L &= V_{n+1}^L \tilde{T}_n^L, \\ A^T W_n^L &= W_{n+1}^L (\tilde{T}_n^L)^T \end{aligned}$$

$\tilde{T}_n^L$  :  $(n+1) \times n$  tri-diagonal matrix with coefficients calculated in Bi-lanczos process

# Bi-CG and QMR

Basis algorithm:

$$AV_n^L = V_{n+1}^L \tilde{T}_n^L$$

Residual condition:

- Bi-CG → Orthogonal condition  $r_n^B \perp K_n(A^T; r_0^*)$
- QMR → Quasi-minimal residual (QMR) property  $\min_{y_n \in \mathbb{R}^n} \|g_1 - \tilde{T}_n^L y_n\|$

Approximate solution:  $x_n = x_0 + V_n^L y_n$

Residual vector:  $r_n = \underbrace{V_{n+1}^L}_{\text{Orthogonal}} \underbrace{(g_1 - \tilde{T}_n^L y_n)}_{\text{Quasi-residual}}, g_1 = \|r_0\| e_1$

× Orthogonal    Quasi-residual



# Bi-CR and Our method

Basis algorithm:  $A$  -biorthogonalization process

- generates the basis vectors  $\{v_1^A, \dots, v_n^A\}$ ,  $\{w_1^A, \dots, w_n^A\}$  of two Krylov subspace,  $K_n(A; r_0)$ ,  $K_n(A^T; r_0^*)$
- $A$  -biorthogonality:  $(w_i, Av_j) = \delta_{ij}$
- Matrix form:

$$\begin{aligned} AV_n^A &= V_{n+1}^A \tilde{T}_n^A, \\ A^T W_n^A &= W_{n+1}^A (\tilde{T}_n^A)^T \end{aligned}$$

$\tilde{T}_n^A$  :  $(n+1) \times n$  tri-diagonal matrix with coefficients calculated in  $A$  -biorthogonalization process







# Bi-CR and Our method

Basis algorithm:

$$AV_n^A = V_{n+1}^A \tilde{T}_n^A$$

Residual condition:

- Bi-CR  Orthogonal condition  $\mathbf{r}_n^R \perp A^T K_n(A^T; \mathbf{r}_0^*)$
- **Our method**  QMR property  $\min_{\mathbf{y}_n \in \mathbb{R}^n} \|\mathbf{g}_1 - \tilde{T}_n^A \mathbf{y}_n\|$

Residual vector:  $\mathbf{r}_n = V_{n+1}^A (\mathbf{g}_1 - \tilde{T}_n^A \mathbf{y}_n)$ ,  $\mathbf{g}_1 = \|\mathbf{r}_0\| \mathbf{e}_1$

**Quasi-residual**



# On Algorithm

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- QMR from Bi-Lanczos process  
 $A$ -biorthogonalization process

Basis algorithm  $\rightarrow$   $\left\{ \begin{array}{l} \text{Bi-Lanczos process} \\ A\text{-biorthogonalization process} \end{array} \right.$

- QMR from Bi-CG  
Bi-CR

Basis algorithm  $\rightarrow$   $\left\{ \begin{array}{l} \text{Bi-CG} \\ \text{Bi-CR} \end{array} \right.$

# QMR from Bi-CG (later QMRBi-CG)

$\mathbf{x}_0^Q$  is an initial guess,  $\mathbf{r}_0^Q = \mathbf{b} - A\mathbf{x}_0^Q$ ,  
 set  $\mathbf{r}_0^B = \mathbf{r}_0^Q$ , choose  $\mathbf{r}_0^{B*}$  (e.g.,  $\mathbf{r}_0^{B*} = \mathbf{r}_0^B$ ),  
 set  $\mathbf{p}_{-1}^{B*} = \mathbf{p}_{-1}^B = \mathbf{d}_{-1}^Q = \mathbf{0}$ ,  
 $\beta_{-1} = 0$ ,  $\tau_{-1} = \|\mathbf{r}_0^B\|$ ,  $\vartheta_{-1} = 0$ ,

for  $n = 0, 1, \dots$ , until convergence, do:

$$\mathbf{p}_n^B = \mathbf{r}_n^B + \beta_{n-1}\mathbf{p}_{n-1}^B, \quad \mathbf{p}_n^{B*} = \mathbf{r}_n^{B*} + \beta_{n-1}\mathbf{p}_{n-1}^{B*},$$

$$\alpha_n = \frac{(\mathbf{r}_n^{B*}, \mathbf{r}_n^B)}{(\mathbf{p}_n^{B*}, A\mathbf{p}_n^B)},$$

$$\mathbf{x}_{n+1}^B = \mathbf{x}_n^B + \alpha_n \mathbf{p}_n^B,$$

$$\mathbf{r}_{n+1}^B = \mathbf{r}_n^B - \alpha_n A\mathbf{p}_n^B, \quad \mathbf{r}_{n+1}^{B*} = \mathbf{r}_n^{B*} - \alpha_n A^T \mathbf{p}_n^{B*},$$

$$\vartheta_n = \frac{\|\mathbf{r}_{n+1}^B\|}{\tau_{n-1}}, \quad c_n = \frac{1}{\sqrt{1+\vartheta_n^2}}, \quad \tau_n = \tau_{n-1}\vartheta_n c_n,$$

$$\mathbf{d}_n^Q = c_n^2 \vartheta_{n-1}^2 \mathbf{d}_{n-1}^Q + c_n^2 \alpha_n \mathbf{p}_n^B, \quad (A\mathbf{d}_n^Q = c_n^2 \vartheta_{n-1}^2 A\mathbf{d}_{n-1}^Q + c_n^2 \alpha_n A\mathbf{p}_n^B),$$

$$\mathbf{x}_{n+1}^Q = \mathbf{x}_n^Q + \mathbf{d}_n^Q, \quad \mathbf{r}_{n+1}^Q = \mathbf{r}_n^Q - A\mathbf{d}_n^Q,$$

$$\beta_n = \frac{(\mathbf{r}_{n+1}^{B*}, \mathbf{r}_{n+1}^B)}{(\mathbf{r}_n^{B*}, \mathbf{r}_n^B)},$$

end

# QMR from Bi-CR (later QMRBi-CR)

$\mathbf{x}_0^{QR}$  is an initial guess,  $\mathbf{r}_0^{QR} = \mathbf{b} - A\mathbf{x}_0^{QR}$ ,

set  $\mathbf{r}_0^R = \mathbf{r}_0^{QR}$ , choose  $\mathbf{r}_0^{R*}$  (e.g.,  $\mathbf{r}_0^{R*} = \mathbf{r}_0^R$ ),

set  $\mathbf{p}_{-1}^{R*} = \mathbf{p}_{-1}^R = \mathbf{d}_{-1}^{QR} = \mathbf{0}$ ,

$\beta_{-1} = 0$ ,  $\tau_{-1} = \|\mathbf{r}_0^R\|$ ,  $\vartheta_{-1} = 0$ ,

for  $n = 0, 1, \dots$ , until convergence, do:

$$\mathbf{p}_n^R = \mathbf{r}_n^R + \beta_{n-1}\mathbf{p}_{n-1}^R, \quad \mathbf{p}_n^{R*} = \mathbf{r}_n^{R*} + \beta_{n-1}\mathbf{p}_{n-1}^{R*},$$

$$(A\mathbf{p}_n^R = A\mathbf{r}_n^R + \beta_{n-1}A\mathbf{p}_{n-1}^R,)$$

$$\alpha_n = \frac{(\mathbf{r}_n^{R*}, A\mathbf{r}_n^R)}{(A^T\mathbf{p}_n^{R*}, A\mathbf{p}_n^R)},$$

$$\mathbf{x}_{n+1}^R = \mathbf{x}_n^R + \alpha_n\mathbf{p}_n^R,$$

$$\mathbf{r}_{n+1}^R = \mathbf{r}_n^R - \alpha_n A\mathbf{p}_n^R, \quad \mathbf{r}_{n+1}^{R*} = \mathbf{r}_n^{R*} - \alpha_n A^T\mathbf{p}_n^{R*},$$

$$\vartheta_n = \frac{\|\mathbf{r}_{n+1}^R\|}{\tau_{n-1}}, \quad c_n = \frac{1}{\sqrt{1+\vartheta_n^2}}, \quad \tau_n = \tau_{n-1}\vartheta_n c_n,$$

$$\mathbf{d}_n^{QR} = c_n^2\vartheta_{n-1}^2\mathbf{d}_{n-1}^{QR} + c_n^2\alpha_n\mathbf{p}_n^R, \quad (A\mathbf{d}_n^{QR} = c_n^2\vartheta_{n-1}^2A\mathbf{d}_{n-1}^{QR} + c_n^2\alpha_n A\mathbf{p}_n^R,)$$

$$\mathbf{x}_{n+1}^{QR} = \mathbf{x}_n^{QR} + \mathbf{d}_n^{QR}, \quad \mathbf{r}_{n+1}^{QR} = \mathbf{r}_n^{QR} - A\mathbf{d}_n^{QR},$$

$$\beta_n = \frac{(\mathbf{r}_{n+1}^{R*}, A\mathbf{r}_{n+1}^R)}{(\mathbf{r}_n^{R*}, A\mathbf{r}_n^R)},$$

end



# Numerical Experiments

CPU	Intel (R) Xeon (TM) 2.66GHz
Memory	512MB
Compiler	Fortran77 Double Precision
Matrix $A$	Matrix Market
Initial guess $x_0$	0
Vector $r_0^*$	The same as $r_0$
Right-hand side $b$	Random
Convergence criterion	$\ r_n\ /\ r_0\  \leq 10^{-6}$ (for WATT2) $\ r_n\ /\ r_0\  \leq 10^{-12}$ (for others)

# Results

Matrix	Iteration			
	Bi-CG	QMR	Bi-CR	QMR
BFW782A				
CDDE5				
DW2048	2295	2280	1716	1717
FS_760_1	163	163	161	161
FIDAP022	2554	2447	1805	1803
JPWH991	82	81	81	82
ORSIRR2	1206	1204	1163	1165
PDE2961	330	330	333	329
PDE900	172	170	161	160
SHERMAN5	2			
WATT2				

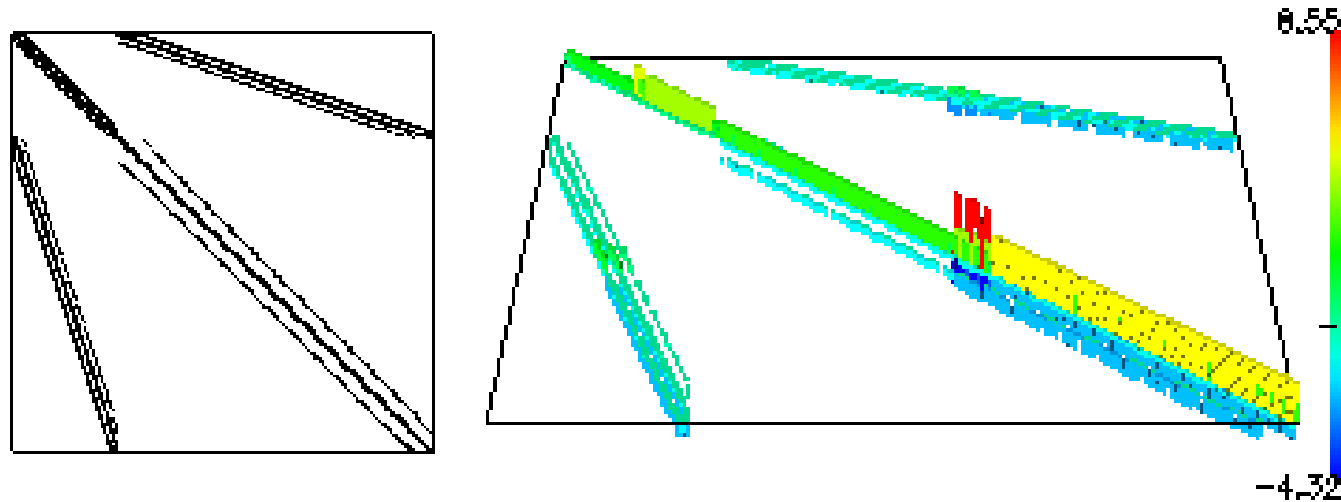
Almost the same iteration count as Bi-CR

Faster convergence than QMRBi-CG

Almost the same iter. count

Matrix Market

# BFW782A: Electrical engineering

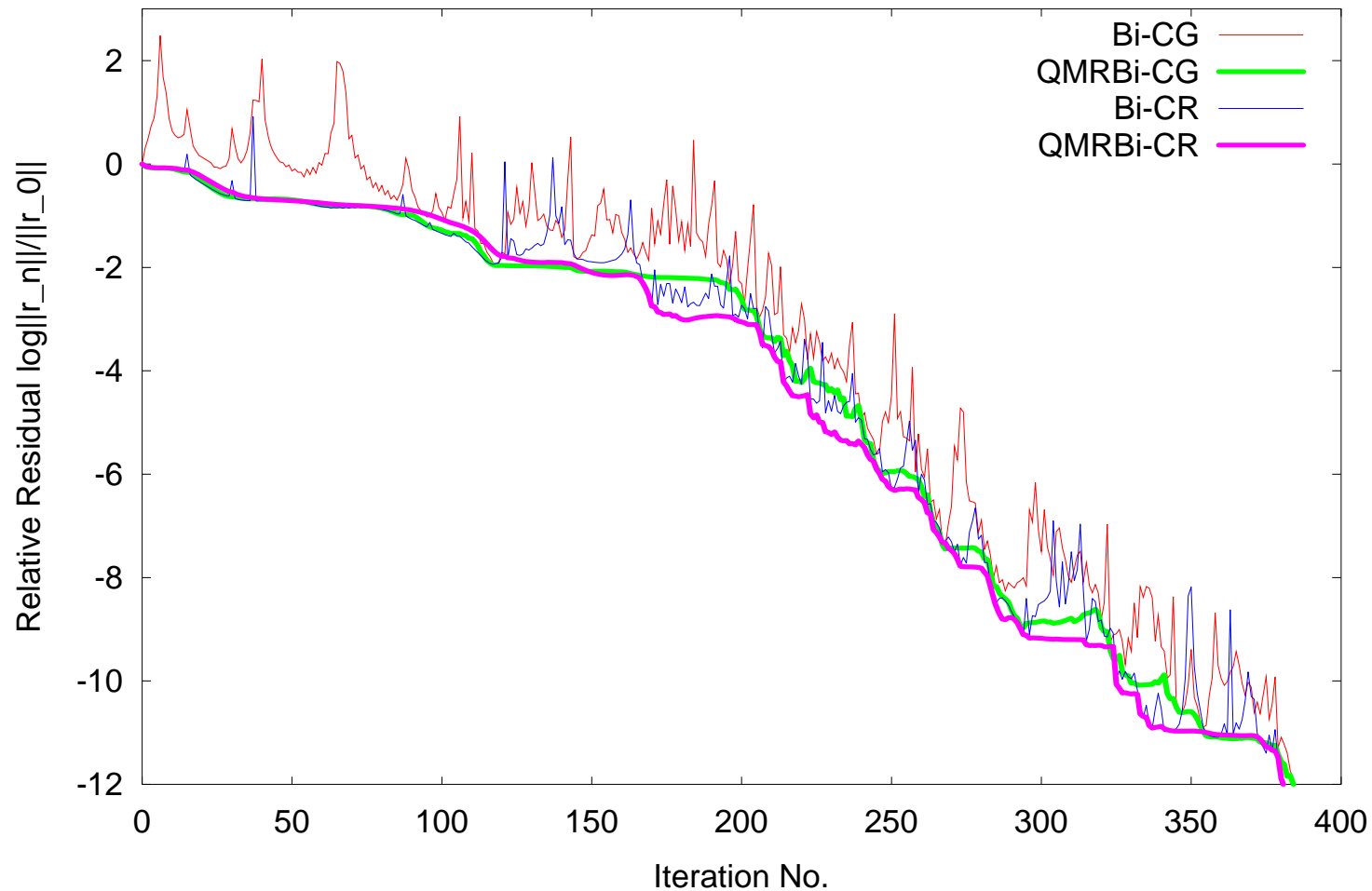


Size	Non Zeros	Type
782	7514	real unsymmetric

Almost the same iter. count

Matrix Market

# BFW782A: Electrical engineering

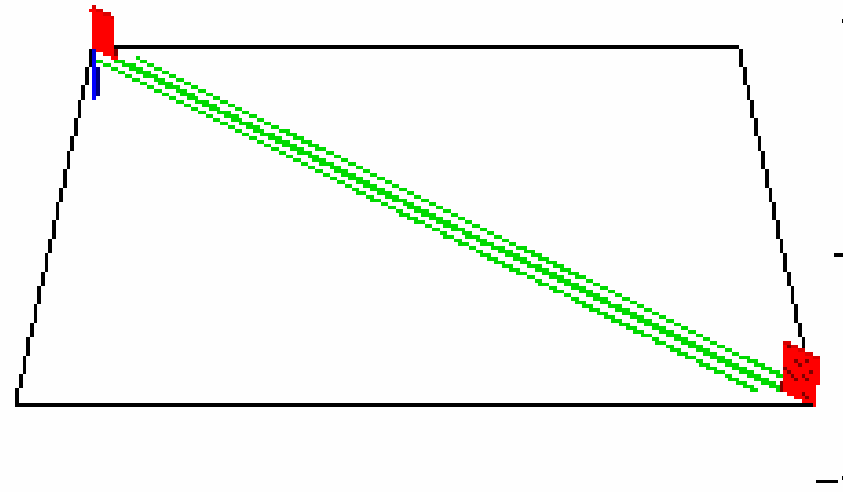
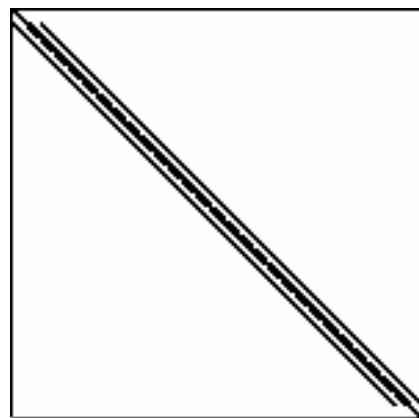




Faster convergence

Matrix Market

# WATT2: Petroleum engineering

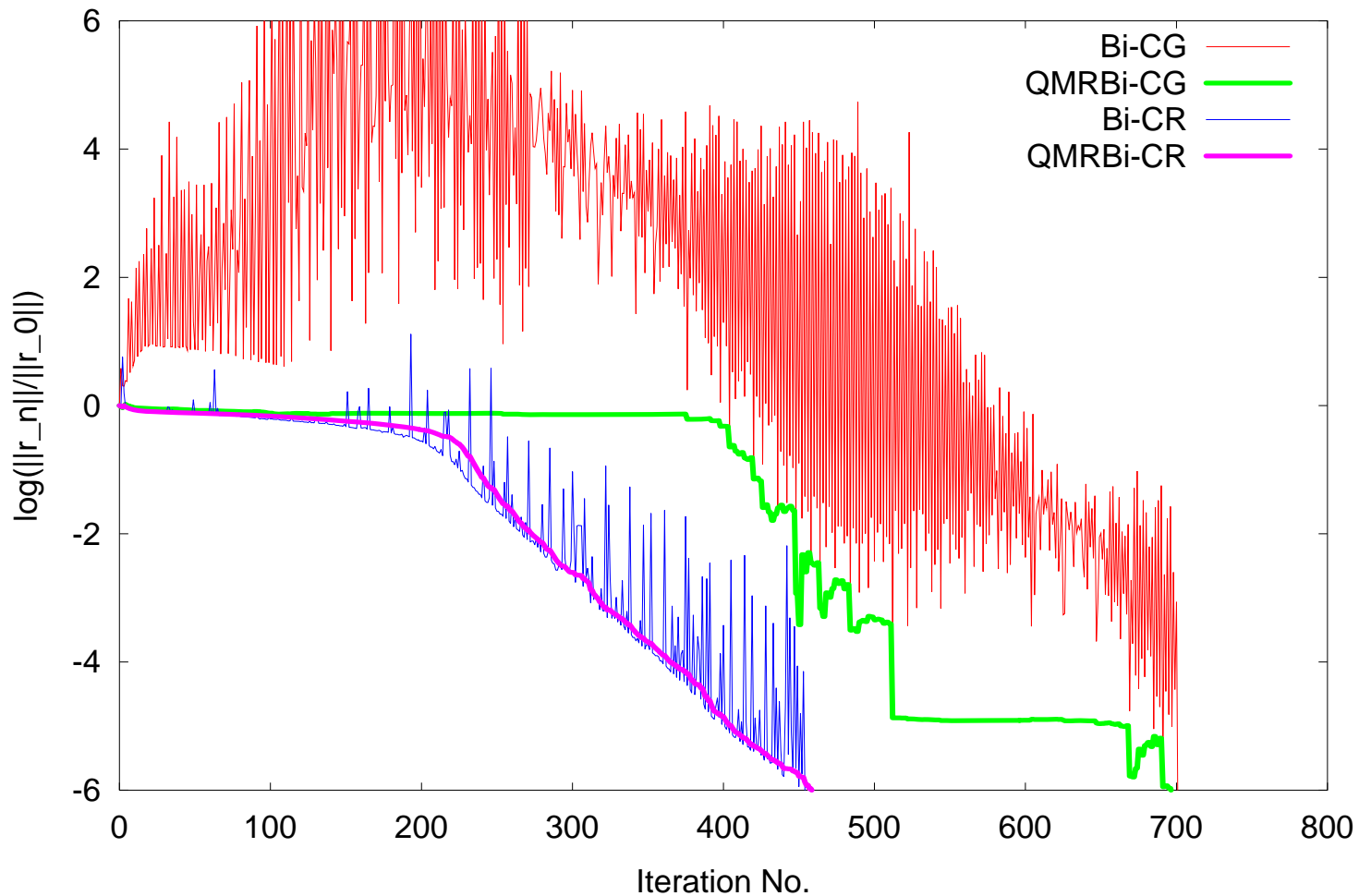


Size	Non Zeros	Type
1856	11550	real unsymmetric

Faster convergence

Matrix Market

# WATT2: Petroleum engineering





# Summary and future plan

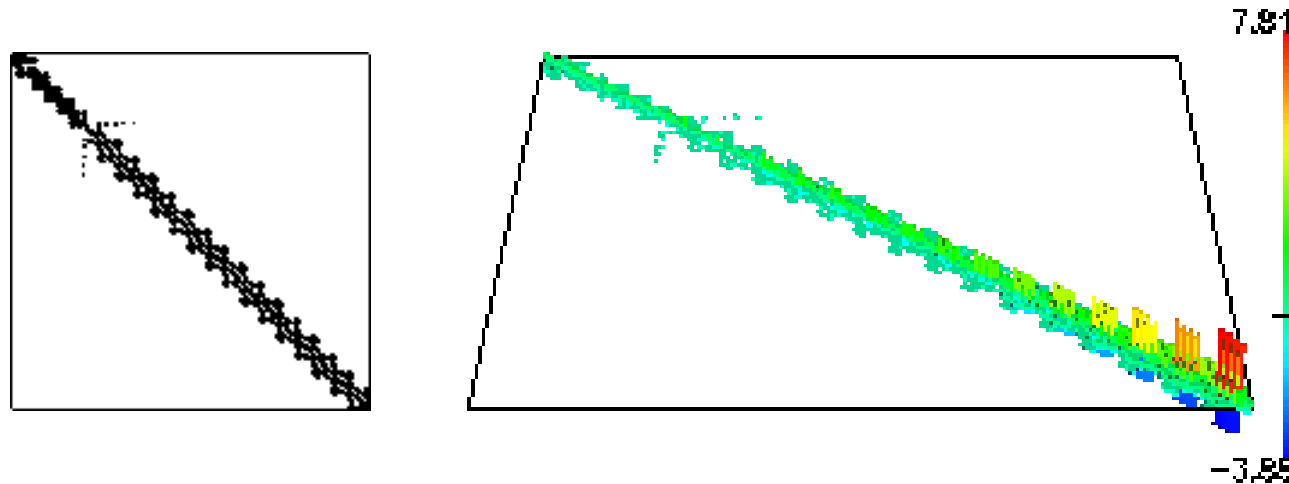
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- We showed a QMR method based on an A-biorthogonalization process.
- From numerical experiments, we confirmed
  - the method has a smoother convergence property compared to Bi-CR.
  - the method has a faster convergence property compared to QMRBi-CG.
- More numerical experiments

Faster convergence

Matrix Market

# fidap022: Finite element modeling

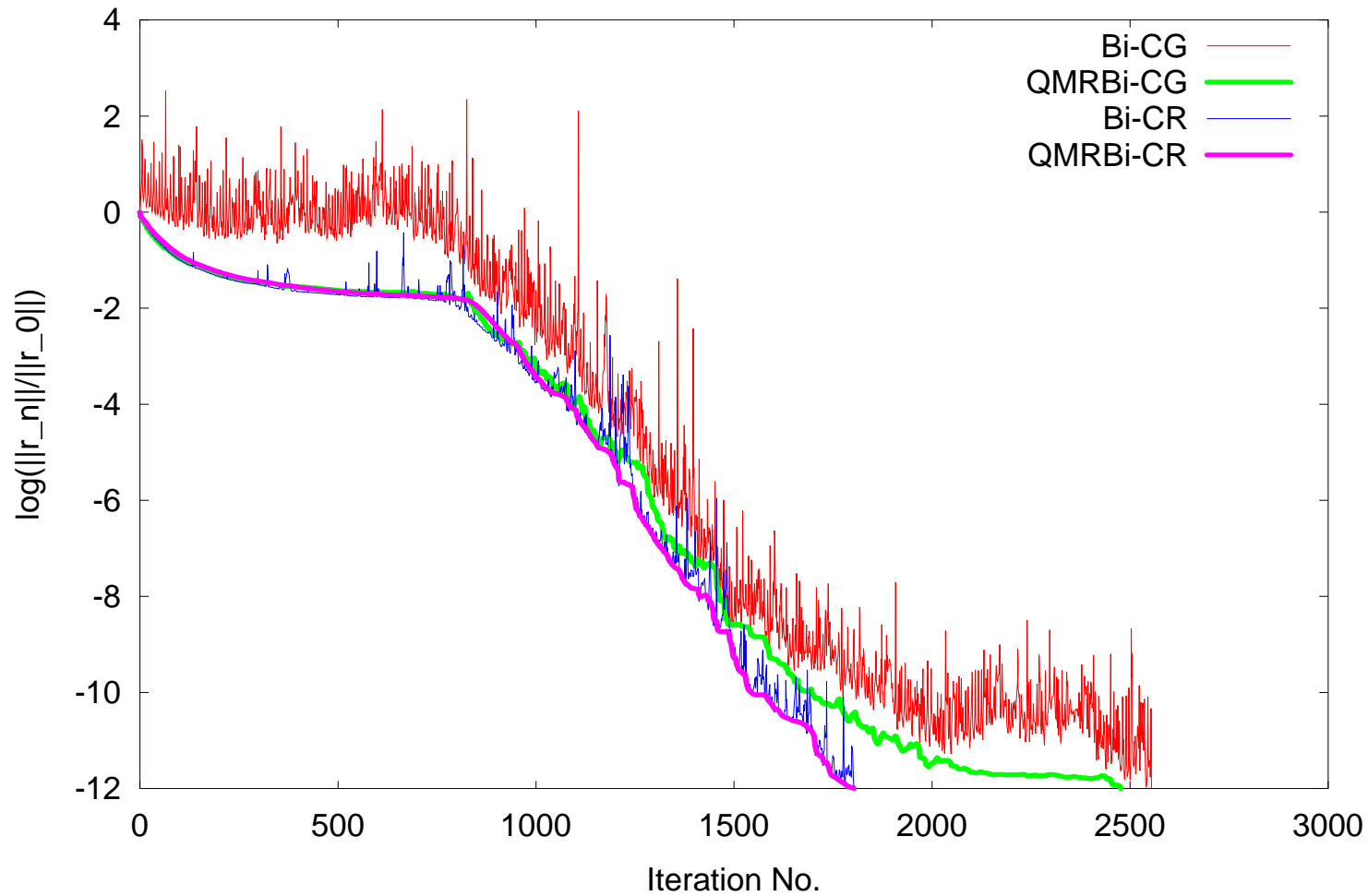


Size	Non Zeros	Type
839	22613	real unsymmetric

Faster convergence

# Matrix Market

## fidap022: Finite element modeling



# sherman5

