

Newton's Method and Efficient, Robust Variants

Philipp Birken

University of Kassel (SFB/TRR 30)
Soon: University of Lund

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Efficient solution of large systems of non-linear PDEs in science
Lyon



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Given error tolerance TOL , initial time t_0 and time step size Δt_0

- For $i = 1, \dots, s$
 - For $k = 0, 1, \dots$ until termination criterion with tolerance $TOL/5$ is satisfied or `MAX_NEWTON_ITER` has been reached
 - Solve linear system up to certain tolerance
 - If `MAX_NEWTON_ITER` has been reached, but the tolerance test has not been passed, repeat time step with $\Delta t_n = \Delta t_n/4$
 - Estimate local error and compute new time step size Δt_{n+1}
 - $t_{n+1} = t_n + \Delta t_n$

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Illustration of Newton's method

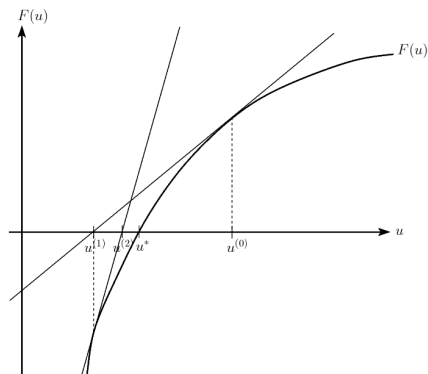


Figure: Illustration of Newton's method in one dimension (left); convergence curve (right)

Newton's method

Assume we solve $\mathbf{F}(\mathbf{x}) = \mathbf{0}$. Given starting value \mathbf{x}^0 , Newton's method is given by:

$$\left. \frac{\partial \mathbf{F}}{\partial \mathbf{x}} \right|_{\mathbf{x}^{(k)}} \Delta \mathbf{x} = -\mathbf{F}(\mathbf{x}^{(k)}),$$
$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \Delta \mathbf{x}, \quad k = 0, \dots$$

- Uses first order approximation of function
- Local quadratic convergence
- Outside of local ball of convergence no statement possible
- Nonlinear system transformed into sequence of linear systems

Standard Assumptions

- Always need Differentiability (at least piecewise)
- For easy convergence theory
 - i) $\mathbf{F}(\mathbf{x}) = 0$ has a solution \mathbf{x}^* .
 - ii) $\mathbf{F}' : \Omega \rightarrow \mathbb{R}^{m \times m}$ is Lipschitz continuous with Lipschitz constant L' .
 - iii) $\mathbf{F}'(\mathbf{x}^*)$ is nonsingular.
- Lower requirements technically possible

- System matrix: $\mathbf{A} = \left[\frac{\mathbf{I}}{\Delta t} - \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \right] \Big|_{\mathbf{x}^{(k)}}$.
- This matrix is sparse, nonnormal, not diagonally dominant and ill conditioned for reasonable Δt .
- Generally unstructured, but symmetric block-sparsity pattern.
- In FVM/low order FEM context: block sizes small even in 3D.
- For DG/high order FEM: Block sizes depend on degree N and dimension d :
 - $(d + 2) \cdot (N + d)! / (N! d!)$
- This makes the design of efficient implicit DG schemes in 3D so difficult, since blocks have couple hundred unknowns

Problem 1: The linear systems are solved exactly

- This implies either a direct solver or an iterative one with extremely small tolerance
- But we want to solve nonlinear systems only approximately
- This is way too costly
- But what happens when we do not solve exactly?

Problem 2: The Jacobian has to be assembled

- Typically very costly to do
- Huge amount of storage for 3D problems
- Need way around this

Let's solve problem 1!

$$\left\| \frac{\partial \mathbf{F}(\mathbf{x})}{\partial \mathbf{x}} \Big|_{\mathbf{x}^{(k)}} \mathbf{d} + \mathbf{F}(\mathbf{x}^{(k)}) \right\| \leq \eta_k \|\mathbf{F}(\mathbf{x}_k)\| \quad (1)$$
$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \mathbf{d}, \quad k = 0, 1, \dots$$

Theorem

Let the standard assumptions hold. Then there is δ such that if $\mathbf{x}^{(0)}$ is in a δ -neighborhood of \mathbf{x}^ , $\{\eta_k\} \subset [0, \eta]$ with $\eta < \bar{\eta} < 1$, then the inexact Newton iteration (1) converges linearly. Moreover,*

- if $\eta_k \rightarrow 0$, the convergence is superlinear and*
- if $\eta_k \leq K_\eta \|\mathbf{F}(\mathbf{x}^{(k)})\|^p$ for some $K_\eta > 0$ and $p \in [0, 1]$, the convergence is superlinear with order $1 + p$.*

$$\eta_k^A = \gamma \frac{\|\mathbf{F}(\mathbf{x}^{(k)})\|^2}{\|\mathbf{F}(\mathbf{x}^{(k-1)})\|^2}, \quad \gamma \in (0, 1]$$

To obtain quadratic convergence, bound sequence away from zero:

$$\eta_k^B = \min(\eta_{max}, \eta_k^A)$$

Definition of η_k is refined to

$$\eta_k^C = \begin{cases} \eta_{max}, & n = 0, \\ \min(\eta_{max}, \eta_k^A), & n > 0, \gamma \eta_{k-1}^2 \leq 0.1 \\ \min(\eta_{max}, \max(\eta_k^A, \gamma \eta_{k-1}^2)) & n > 0, \gamma \eta_{k-1}^2 > 0.1 \end{cases}$$

to avoid volatile decreases in η_k . To avoid oversolving

$$\eta_k = \min(\eta_{max}, \max(\eta_k^C, 0.5\tau/\|\mathbf{F}(\mathbf{x}^{(k)})\|)).$$



Now, let's solve problem 2!

- Freeze the Jacobian and periodically recompute periodically
- Thus we use approximation

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \mathbf{A}(\mathbf{x}^{(k)})^{-1} \mathbf{F}(\mathbf{x}^{(k)})$$

- Meaning we solve a different linear equation system
- Only linear convergence, provided that $\rho(\mathbf{I} - \mathbf{A}(\mathbf{x})^{-1} \frac{\partial \mathbf{F}}{\partial \mathbf{x}})$ is small enough
- This is **not a good solution for problem 2!**

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Let's give problem 2 another try!

- Solve iterative systems using Krylov subspace method (e.g. GMRES)
- These do not need Jacobian, only matrix vector products.
- Approximate $\frac{\partial \mathbf{F}}{\partial \mathbf{x}} \mathbf{q}$ by finite differences:

$$\mathbf{A}\mathbf{q} = \frac{\partial \mathbf{F}(\mathbf{x}^{(k)})}{\partial \mathbf{x}} \mathbf{q} \approx \frac{\mathbf{F}(\mathbf{x}^{(k)} + \epsilon \mathbf{q}) - \mathbf{F}(\mathbf{x}^{(k)})}{\epsilon}.$$

- More expensive than sparse matrix vector products.
- Immense flexibility
- Since we solve the correct linear equation system, quadratic convergence is retained, thus fast method!

Theorem

Let the standard assumptions hold. Then there are δ , $\bar{\sigma}$, C_G such that if \mathbf{x}_0 is in a δ -neighborhood of $\bar{\mathbf{x}}^$ and the sequences $\{\eta_k\}$ and $\{\epsilon_k\}$ satisfy*

$$\sigma_n = \eta_n + C_G \epsilon_n \leq \bar{\sigma},$$

then the Jacobian free Newton-GMRES iteration converges linearly.

Moreover,

- if $\sigma_k \rightarrow 0$, the convergence is superlinear and*
- if $\sigma_k \leq K_\eta \|\mathbf{F}(\mathbf{x}_k)\|^p$ for some $K_\eta > 0$ and $p \in [0, 1]$, the convergence is superlinear with order $1 + p$.*

Given error tolerance TOL , initial time t_0 and time step size Δt_0

- For $i = 1, \dots, s$
 - For $k = 0, 1, \dots$ until termination criterion with tolerance $TOL/5$ is satisfied or `MAX_NEWTON_ITER` has been reached
 - Determine Eisenstat-Walker relative tolerance
 - Solve linear system using preconditioned GMRES
 - If `MAX_NEWTON_ITER` has been reached, but the tolerance test has not been passed, repeat time step with $\Delta t_n = \Delta t_n/4$
 - Estimate local error and compute new time step size Δt_{n+1}
 - $t_{n+1} = t_n + \Delta t_n$

Note: Puts additional bound on time step via nonlinear solver

Efficiency of different Newton schemes

JFNK-FT	JFNK-EW	Newton-type-FT	Newton-type-EW
3.0	4.1	0.7	0.9

Table: Upper bounds of convergence radius for Shu vortex problem in terms of CFL numbers. FT stands for a fixed tolerance of 10^{-2} , EW for Eisenstat-Walker.

	JFNK-FT	JFNK-EW	Newton-type-FT	Newton-type-EW
Iter.	32,793	6,821	45,531	10,101
CPU	17,394	4,566	19,920	10,672

Table: Comparison of efficiency of different Newton variants. SDIRK2, $TOL = 10^{-2}$

Newton convergence: Unsteady TEMPO

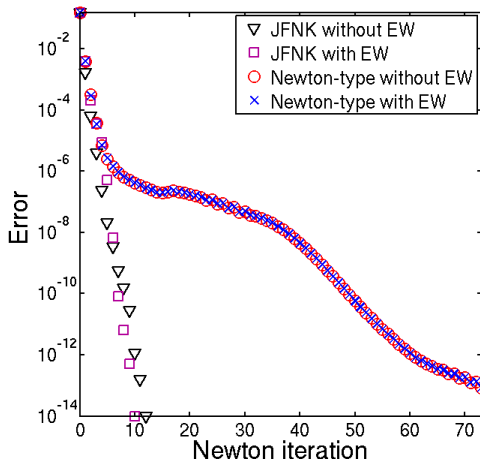


Figure: Convergence of different Newton schemes for one time step during an unsteady calculation

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Newton convergence: TEMPO for steady states

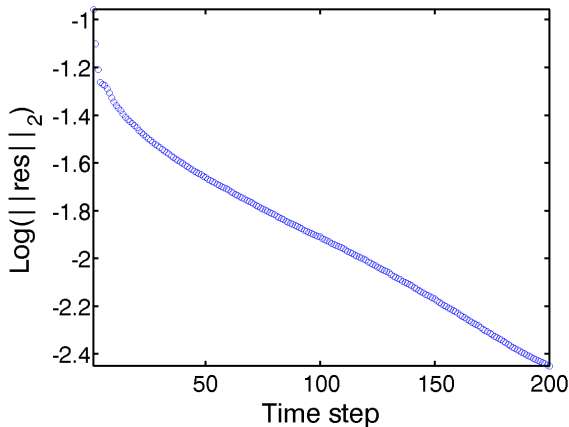


Figure: Convergence to steady state of a damped scheme of Newton-type

Multigrid convergence: UFLO103 on structured grid

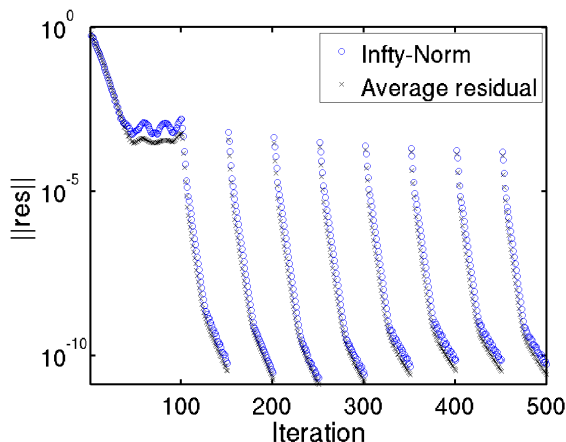


Figure: UFLO103 convergence, first 100 steps using the steady state solver, then 50 iteration of dual time stepping per time step

Multigrid convergence: DLR TAU

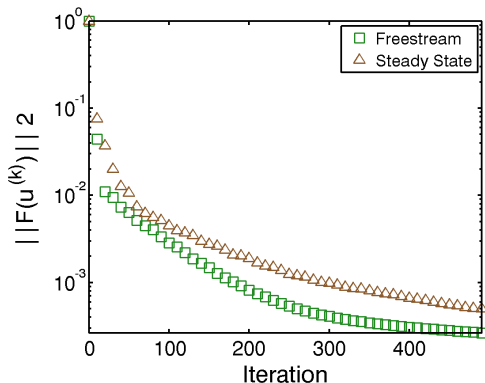


Figure: DLR TAU dual time stepping for two different systems.

FAS in TAU converges to something else. Wrong BC on coarse grids?



Steady States

- Multigrid fast
- Newton slow

Unsteady problems

- Here we expect significantly faster convergence
- Multigrid marginally, if at all, faster, not fast on unstructured grids
- Newton significantly faster than for steady state

Multigrid

- Dual time stepping typically implies reusing the steady state algorithm without changes
- Thus less than optimal multigrid convergence
- Redesign multigrid (see B., *Optimizing Runge-Kutta smoothers for unsteady flow problems*, ETNA, 2012)

Newton

- Very good scheme: Jacobian-Free Newton-GMRES with good parallel preconditioner
- Multigrid candidate for preconditioner (see above)

Compare *Solving nonlinear systems inside implicit time integration schemes for unsteady viscous flows*, P. Birken, pp. 57-71 in R. Ansorge, H. Bijl, A. Meister, T. Sonar (editors), *Numerics of Nonlinear Hyperbolic Conservation Laws*, Notes on Numerical Fluid Mechanics, Springer

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Choice of initial guess

- Good choice of initial guess important
- Without that, we might have divergence
- With it, we could be close to the solution and need very few steps
- In unsteady time stepping, last value often good choice
- But: For huge time steps, this might not be in radius of convergence (see flow chart)
- Extrapolation of old values can help
- Stage value predictors other possibility

- Problem: Local convergence
- Solution globalization strategy via line search:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \lambda \Delta \mathbf{x}^{(k)}, \quad \lambda \in [0, 1]$$

- Popular choice: Armijo line search

$$\|\mathbf{F}(\mathbf{x}^{(k+1)})\| < (1 - \alpha\lambda)\|\mathbf{F}(\mathbf{x}^{(k)})\|, \quad 0 < \alpha \ll 1$$

- For example, $\alpha = 10^{-4}$ is a suitable choice.
- Search for suitable λ done in trivial way by starting with 1 and dividing by 2 if condition not satisfied.
- This method is linearly convergent
- When close to solution, full steps with $\lambda = 1$ can be taken and original convergence rate recovered

- JFNK approach extremely flexible (think change of space discretization)
- Very modular, thus high reusability
- Avoids storing the Jacobian
- Need vector data structure at some point
- Might be good to have solution in that instead of grid based structure
- Parallelization hinges on space discretization and Krylov solver
- Software: PETSc, SUNDIALS, TRILINOS, TEMPO (soon)

- Convergence of Krylov subspace methods (GMRES) depends strongly on matrix.
- Transform problem to get better convergence.
- Use right preconditioning, since residual is unchanged (inexact JFNK)

$$\mathbf{A}\mathbf{P}\mathbf{y} = \mathbf{b}, \quad \mathbf{y} = \mathbf{P}^{-1}\Delta\mathbf{x}$$

- In a JFNK scheme, we do not compute the matrix a priori.
- Need to compute all parts of matrix needed for preconditioner.
- This is where things get difficult for the first time

- Newton locally quadratic convergent
- Problem 1: Need to solve equation exactly
- Solved by inexact Newton scheme
- Choosing proper termination criteria key to efficiency!
- Problem 2: Need to store and compute Jacobian
- Solved by JFNK approach
- Multigrid is main competitor
- Can be used inside a Newton scheme
- Preconditioning is a key issue.

- C. T. Kelley. Iterative Methods for Linear and Nonlinear Equations. SIAM, Philadelphia, PA, 1995
- J. E. Dennis and R. B. Schnabel. Numerical Methods for Unconstrained Optimization and Nonlinear Equations. Classics in Applied Mathematics. SIAM, Philadelphia, 1996
- P. Deuffhard. Newton Methods. Springer, 2004
- E. Hairer and G. Wanner. Solving Ordinary Differential Equations II. Springer, Berlin, 2nd edition, 2004
- B., Numerical methods for the unsteady compressible Navier-Stokes equations, Habilitation Thesis, 2012, University of Kassel