A Residual Smoothing Strategy for Accelerating Newton Method Continuation

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Motivation

- Newton-Krylov methods have become popular for solving difficult/stiff CFD problems
 - Krylov methods provide robust linear system convergence
 - Newton method provides quadratic convergence enabling convergence to low residual tolerances
- Newton methods require continuation for most problems
- Most of the time spent for solving CFD problems is spent in the continuation process
- Continuation methods can stall due to local effects
 - "Unbalanced nonlinearities"
 - Attempts made to break up into smaller nonlinear problems
 - ASPIN, RASPIN

Newton Method

- To solve: R(w) = 0
- Linearize to get Jacobian dR/dw
- Take Newton steps as:

$$[dR(w^n)/dw^n] \Delta w^n = - R(w^n)$$

w^{n+1} = w^n + \alpha \Delta w^n

with $0 < \alpha < 1$ as determined by (backtracking) line search to minimize $||R(w^{n+1})||_2$

- Introduce pseudo-time term and solve $[M(w^{n+1} - w^n) / \Delta \tau + R(w^{n+1}) = R_t(w^{n+1}) = 0$
- Take Newton steps as:

 $[M/\Delta \tau + dR(w^n)/dw^n] \Delta w^n = - R(w^n)$ w^{n+1} = w^n + $\alpha \Delta w^n$

with $0 < \alpha < 1$ as determined by (backtracking) line search to minimize $||R_t(w^{n+1})||_2$

M is a suitable mass matrix

 $\Delta \tau$ is the pseudo time step (local time step = CFL $\Delta \tau_{explicit}$)

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Note: $R(w^n) = R_t(w^n) \dots but R(w^{n+1}) \neq R_t(w^{n+1})$

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with $0 < \alpha < 1$ as determined by (backtracking) line search to minimize $||R_t(w^{n+1})||_2$

 Δw is guaranteed to be a descent direction for $||R_t||_2$ provided [M/ $\Delta \tau$ + dR/dw] is an exact linearization of R_t

 $[M/\Delta\tau + dR(w^n)/dw^n] \Delta w^n = - R(w^n)$

- Limit as ∆t >> 1 : Recover Newton scheme
 [dR(wⁿ)/dwⁿ] ∆wⁿ = R(wⁿ)
- Limit as $\Delta \tau \ll 1$: Recover point explicit scheme $[M/\Delta \tau] \Delta w^n = -R(w^n) \text{ or } \Delta w^n = -\Delta \tau R(w^n)$

M is simply cell volume for finite-volume scheme and is absorbed in $\Delta \tau$ above for simplicity

Pseudo-Transient Controller

- Magnitude of $\Delta\tau$ (or CFL) controlled by success/failure of line search
 - Initial CFL \sim 1
 - Line search result: α = 1
 - Line search result: α < 0.1
 - Otherwise

CFL = CFL * 1.5 CFL = CFL / 10 CFL = constant

- Common failure mode: CFL \rightarrow 0

 $\Delta w^n = -\Delta \tau R(w^n)$ also $\rightarrow 0$

- Observation:
 - Common local nonlinear smoothers (block Jacobi, line Jacobi, Gauss-Seidel) have no difficulties reducing residuals in cases where PTC fails in above mode
 - Explicit scheme is poor choice for anisotropic problems (line smoothers preferred)

Desired Behavior

good for rapid initial residual reduction

• In the limit CFL << 1

 $\Delta w^n = - D^{-1} R(w^n)$

- where D is some preconditioner/smoother
 - possibly nonlinear
 - Independent of CFL or $\Delta\tau$
- Possible formulation:

$$\left[\alpha(\Delta\tau)D + \beta(\Delta\tau)\frac{\partial R}{\partial w}\right]\Delta w^n = -R(w^n)$$

with, for example....

$$\alpha(\Delta \tau) = \frac{1}{1+\Delta \tau} \quad \beta(\Delta \tau) = \frac{\Delta \tau}{1+\Delta \tau}$$

Still recovers Newton scheme for $\Delta \tau >> 1$

Disadvantages

$$\left[\alpha(\Delta\tau)D + \beta(\Delta\tau)\frac{\partial R}{\partial w}\right]\Delta w^n = -R(w^n)$$

- Left-hand side matrix is modified
 - May require modification of linear solver techniques especially for intermediate values of $\Delta\tau$
- Left-hand side matrix is no longer exact linearization of RHS
 - Descent direction for line search not guaranteed

Alternate Approach

- Leave LHS (Jacobian) unchanged
- Modify RHS as:

$$\left[\frac{M}{\Delta\tau} + \frac{\partial R}{\partial w}\right] \Delta w^n = -R(w^n) - D^{-1} \frac{M}{\Delta\tau} R(w^n)$$

- For
$$\Delta \tau \ll 1$$
: $\frac{M}{\Delta \tau} \Delta w^n = -D^{-1} \frac{M}{\Delta \tau} R(w^n)$

- For
$$\Delta \tau >> 1$$
:

$$\frac{\partial R}{\partial w} \Delta w^n = -R(w^n)$$

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For
$$\Delta \tau \ll 1$$
: $\frac{M}{\Delta \tau} \Delta w^n = -D^{-1} \frac{M}{\Delta \tau} R(w^n)$
For $\Delta \tau \gg 1$: $\frac{\partial R}{\partial w} \Delta w^n = -R(w^n)$

Residual Smoothing Interpretation

$$\left[\frac{M}{\Delta\tau} + \frac{\partial R}{\partial w}\right] \Delta w^n = -R(w^n) - D^{-1}\frac{M}{\Delta\tau}R(w^n)$$

- $D^{-1}M/\Delta\tau$ is a non-dimensional operator with a non-trivial stencil (due to D^{-1})
- RHS may be interpreted as a smoothed residual vector

$$\left[\frac{M}{\Delta\tau} + \frac{\partial R}{\partial w}\right] \Delta w^n = -\left[I + D^{-1}\frac{M}{\Delta\tau}\right] R(w^n) = R_{sm}(w^n)$$

smoothing operator

Residual Smoothing Advantages

$$\left[\frac{M}{\Delta\tau} + \frac{\partial R}{\partial w}\right] \Delta w^n = -\left[I + D^{-1}\frac{M}{\Delta\tau}\right] R(w^n) = R_{sm}(w^n)$$

- Simple to implement:

- Add precomputed correction Δw =-D⁻¹R(w) to RHS and scale by M/ $\Delta \tau$
- LHS Jacobian is unchanged from original scheme
 - Make use of existing linear solvers
- LHS Jacobian is exact linearization of RHS
 - Line search descent direction is guaranteed

$$R_{sm}(w^{n+1}) = \frac{M}{\Delta \tau}(w^{n+1} - w^n) + R(w^{n+1}) + D^{-1}\frac{M}{\Delta \tau}R(w^n)$$

Smoothing term always evaluated at wⁿ (vanishes in linearization)

Residual Smoothing Advantages

- Line search minimizes $||R_{sm}||_2$ instead of $||R_t||_2$
- For $\Delta \tau >> 1$ these are the same
- For $\Delta \tau << 1$ Line search usually takes full update since we have:

$$R_{sm}(w^{n+1}) \sim \frac{M}{\Delta \tau} (\Delta w^n) + R(w^{n+1}) + D^{-1} \frac{M}{\Delta \tau} R(w^n)$$

small wrt to other terms

- and the the solution $\Delta w^n = -D^{-1}R(w^n)$ implies $R_{sm}(w^n + \Delta w^n) \sim 0$

Generalization and Implementation $\left[\frac{M}{\Delta \tau} + \frac{\partial R}{\partial w}\right] \Delta w^{n} = -R(w^{n}) - D^{-1} \frac{M}{\Delta \tau} R(w^{n})$

- Implement by adding precomputed update as source term on RHS: $\Delta w^{sm} = -D^{-1}R(w^n)$

– and rescale by M/ $\Delta\tau$

- In practice Δw^{sm} can be the result of any sequence of nonlinear smoothing operations
 - Multistage Runge-Kutta designed for smoothing (Jameson 1981)
 - Any number of nonlinear (FAS) multigrid cycles

Results

- Implemented in unstructured mesh CFD code NSU3D
 - Highly anisotropic meshes in near wall region
 - Extract line structures for implicit line solve
 - Nonlinear solver:
 - 3 stage line-implicit Runge-Kutta
 - Used as solver, or smoother for agglomeration Multigrid
 - Newton-Krylov Solver
 - Pseudo-transient continuation with line search and CFL controller
 - Linear system solved by linear MG: Linear residual reduction = 0.01
 - Original version (unsmoothed)
 - Smoothed version: 5 cycles of 3-stage line RK to compute smoothing term





Results: Test Case 1





- Transonic flow over wing-body configuration
- Solution of Reynolds-Averaged Navier-Stokes Equations (RANS):
 - 2nd order finite-volume
 - Mach=0.75, Incidence=0°, Re=3 million, Spalart-Allmaras Turbulence model
 - 1.2 million point mesh (mixed tets, prisms)
 - Highly anisotropic (1:10,000) near wall

Convergence of Nonlinear Solvers

• 3 stage line-implicit Runge Kutta smoother



Single Grid Solver

4-Level FAS Multigrid Solver

- Relatively monotone convergence in both cases
- As expected, multigrid solver 10X faster

Convergence of PTC Newton-Krylov Original (Unsmoothed)



- 80 nonlinear cycles, 2063 total Krylov vectors
- Achieves quadratic convergence at end

Convergence of PTC Newton-Krylov Original (Unsmoothed)



- Some linear systems at startup (low CFL) are difficult to solve !
- CFL only climbs rapidly after ~50 nonlinear cycles (out of 80)

Convergence of PTC Smoothed Newton-Krylov



- All settings identical to previous case
- Smoothing constructed using 5 nonlinear cycles of 3-stage line-RK
 - Requires 10% of overall solution time
- Nonlinear cycles reduced from 80 to 43
- Cumulative Krylov vectors reduces from 2068 to 888

Convergence of PTC Smoothed Newton-Krylov



- Near monotonic rise of CFL in continuation process
- No difficult linear systems (as determined by number of Krylov vectors)

Is it Smoothing or Solving ?



Smoothing = 5 single grid nonlinear cycles

Smoothing = 5 multigrid nonlinear cycles

- Multigrid and single grid smoothing produce similar overall convergence
- Supporting evidence that smoothing is effective mechanism
 - Recall: FAS MG 10X faster than single grid nonlinear solver

Is it Smoothing or Solving ?



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Test Case 2: Time-Dependent 4-Bladed Rotor



first 5 time steps

- RANS equations with SA turbulence model
- 2 million point mesh with highly anisotropic prisms near blade surfaces
- BDF2 time discretization: 1 degree time step
- Rotor started impulsively in freestream flow (tip Mach number ~ 0.9)
- FAS Multigrid converges initial and subsequent time steps at similar rates

Time-Dependent Test Case



Original (unsmoothed) Newton

- Newton-Krylov method requires lengthy continuation to converge first time step: 120 nonlinear cycles
 - Impulsively started rotor
- Subsequent time steps converge rapidly: < 10 nonlinear cycles
 - Good initial guess from previous time step

Original (unsmoothed) Newton-Krylov



- First time step
 - 120 nonlinear steps, 1600 Krylov vectors
- Third time step
 - 9 nonlinear steps, 150 Krylov vectors

Smoothed Newton-Krylov



- Smoothing constructed using 5 cycles of 3-stage line RK
- First time step solution reduced from
 - 120 to 20 nonlinear cycles
 - 1600 to 220 Krylov vectors
- Subsequent time steps similar to unsmoothed case
- Convergence of all time steps is more consistent

Original (unsmoothed) Newton-Krylov



- First time step generates
 - Difficult linear systems
 - Slow CFL growth

Smoothed Newton-Krylov



- Smoothed solver produces monotonic CFL growth
- More similar convergence for all time steps

Conclusions

- Continuation for Newton methods in CFD are often problematic
 - Majority of solver time spent far from domain of quadratic convergence
 - Pseudo-transient continuation can lead to ill-conditioned systems generated by "bad" solution states
- Addition of source term based on nonlinear smoothing can accelerate PTC-Newton schemes
 - Empirical evidence points to smoothing (vs. solving) as dominant mechanism
- Formulation prevents stalling due to small CFL values
 - Reverts to local nonlinear smoother in limit CFL << 1
- Difficulties may still occur if strong nonlinearities arise in intermediate regions 1 << CFL << ∞
 - Future work...

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