## MATH 676

## Finite element methods in scientific computing

Wolfgang Bangerth, Texas A\&M University

## Lecture 31.5:

## Nonlinear problems

## Part 1: Introduction

## Nonlinear problems

## Reality is nonlinear.

Linear equations are only approximations.

## Nonlinear problems

## Reality is nonlinear.

## Linear equations are only approximations.

Linear equations typically assume that something is small:

- Poisson equation for displacement of a membrane Assumption: small displacement
- Stokes equation

Assumption: slow flow, incompressible medium

- Maxwell equations

Assumption: Small electromagnetic field strength

## Fluid flow example, part 1

## Consider the Stokes equations:

$$
\begin{array}{ll}
\rho \frac{\partial u}{\partial t}-v \Delta u+\nabla p & =f \\
\nabla \cdot u & =0
\end{array}
$$

These equations are the small-velocity approximation of the nonlinear Navier-Stokes equations:

$$
\begin{array}{ll}
\rho\left(\frac{\partial u}{\partial t}+u \cdot \nabla u\right)-v \Delta u+\nabla p & =f \\
\nabla \cdot u & =0
\end{array}
$$

## Fluid flow example, part 2

The Navier-Stokes equations

$$
\begin{array}{ll}
\rho\left(\frac{\partial u}{\partial t}+u \cdot \nabla u\right)-v \Delta u+\nabla p & =f \\
\nabla \cdot u & =0
\end{array}
$$

are the small-pressure approximation of the variable-density Navier-Stokes equations:

$$
\begin{array}{ll}
\rho\left(\frac{\partial u}{\partial t}+u \cdot \nabla u\right)-v \Delta u+\nabla p & =f \\
\nabla \cdot(\rho u) & =0
\end{array}
$$

## Fluid flow example, part 3

The variable-density Navier-Stokes equations can be further generalized:

- The viscosity really depends on
- pressure
- strain rate
- Friction converts mechanical energy into heat
- Viscosity and density depend on temperature
- ...


## 1d elastic deformation example

Consider a 1d rubber band:

- Clamped at the ends
- Deformed perpendicularly by a force $f(x)$
- Leading to a perpendicular displacement $u(x)$



## 1d elastic deformation example



If a material is linearly elastic, then the energy stored in a deformation is proportional to its elongation:

$$
\begin{aligned}
E_{\text {deformation }}(u) & =\lim _{\Delta x \rightarrow 0} \sum_{j=1, \Delta x=\frac{(b-a)}{N}}^{N} A\left(\sqrt{(\Delta x)^{2}+\left(u^{\prime}\left(x_{j}\right) \Delta x\right)^{2}}-\Delta x\right) \\
& =\int_{a}^{b} A\left(\sqrt{(d x)^{2}+\left(u^{\prime}(x) d x\right)^{2}}-d x\right)=\int_{a}^{b} A\left(\sqrt{1+\left(u^{\prime}(x)\right)^{2}}-1\right) d x
\end{aligned}
$$

## 1d elastic deformation example

## The total energy is a sum of two terms:

- the deformation energy
- the work against an external force

$$
\begin{aligned}
E(u) & =E_{\text {deformation }}+E_{\text {potential }} \\
& =\int_{a}^{b} A\left(\sqrt{1+\left(u^{\prime}(x)\right)^{2}}-1\right) d x-\int_{a}^{b} f(x) u(x) d x \\
& =\int_{a}^{b}\left[A\left(\sqrt{1+\left(u^{\prime}(x)\right)^{2}}-1\right)-f(x) u(x)\right] d x
\end{aligned}
$$

## 1d elastic deformation example

We seek that displacement $u(x)$ that minimizes the energy

$$
E(u)=\int_{a}^{b}\left[A\left(\sqrt{1+\left(u^{\prime}(x)\right)^{2}}-1\right)-f(x) u(x)\right] d x
$$

This is equivalent to finding that point $u(x)$ for which every infinitesimal variation $\varepsilon v(x)$ leads to the same energy:

$$
\lim _{\epsilon \rightarrow 0} \frac{1}{\epsilon}[E(u+\epsilon v)-E(u)]=0 \quad \forall v \in H_{0}^{1}
$$

In other words:

$$
\int_{a}^{b}\left(A \frac{v^{\prime}(x) u^{\prime}(x)}{\sqrt{1+\left(u^{\prime}(x)\right)^{2}}}-v(x) f(x)\right) d x=0 \quad \forall v \in H_{0}^{1}
$$

## 1d elastic deformation example

We seek that displacement $u(x)$ that satisfies

$$
\int_{a}^{b}\left(A \frac{v^{\prime}(x) u^{\prime}(x)}{\sqrt{1+\left(u^{\prime}(x)\right)^{2}}}-v(x) f(x)\right) d x=0 \quad \forall v \in H_{0}^{1}
$$

The strong form of this equation is:

$$
-\left(A \frac{u^{\prime}(x)}{\sqrt{1+\left(u^{\prime}(x)\right)^{2}}}\right)^{\prime}=f(x)
$$

In multiple space dimensions, this generalizes to this:

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

This is often called the minimal surface equation.

## Minimal surface vs. Poisson equation

Note: If the vertical displacement of the membrane is small and smooth, then

$$
|\nabla u|^{2} \ll 1
$$

In this case, the (nonlinear) minimal surface equation

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

can be approximated by the (linear) Poisson equation:

$$
-\nabla \cdot(A \nabla u)=f
$$

## What makes this complicated?

Start with the minimal surface equation

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

and its weak form:

$$
\left(\nabla \phi, A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=(\phi, f) \quad \forall \phi \in H_{0}^{1}
$$

Let's see what happens if we just discretize as always using

$$
u_{h}(x)=\sum_{j} U_{j} \phi_{j}(x)
$$

## What makes this complicated?

Start with the minimal surface equation

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

and discretize as always:

$$
\left(\nabla \phi_{i}, A \frac{\nabla \sum_{j} U_{j} \phi_{j}}{\sqrt{1+\left|\nabla \sum_{j} U_{j} \phi_{j}\right|^{2}}}\right)=\left(\phi_{i}, f\right) \quad \forall i=1 \ldots N
$$

We can pull some coefficients and sums out:

$$
\sum_{j}\left(\nabla \phi_{i}, A \frac{\nabla \phi_{j}}{\sqrt{1+\left|\sum_{j} U_{j} \nabla \phi_{j}\right|^{2}}}\right) U_{j}=\left(\phi_{i}, f\right) \quad \forall i=1 \ldots N
$$

This is a (potentially large) nonlinear system of equations!

## What makes this complicated?

Start with the minimal surface equation

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Discretizing as usual yields a system of nonlinear equations:

$$
\sum_{j}\left(\nabla \phi_{i}, A \frac{\nabla \phi_{j}}{\sqrt{1+\left|\sum_{j} U_{j} \nabla \phi_{j}\right|^{2}}}\right) U_{j}=\left(\phi_{i}, f\right) \quad \forall i=1 \ldots N
$$

This could be written as

$$
A(U) U=F
$$

Problem: We don't know how to solve such systems directly. I.e., we know of no finite sequence of steps that yields the solution of general systems of nonlinear systems!

## Nonlinear problems

In general: There is no finite algorithm to find simultaneous roots of a general system of nonlinear equations:

$$
\begin{gathered}
f_{1}\left(x_{1}, \ldots, x_{N}\right)=0 \\
f_{2}\left(x_{1}, \ldots, x_{N}\right)=0 \\
\vdots \\
f_{N}\left(x_{1}, \ldots, x_{N}\right)=0
\end{gathered}
$$

Or more concisely:

$$
F(x)=0
$$

However: Such algorithms exist for the linear case, e.g., Gaussian elimination.

## Nonlinear problems

In fact: There is no finite algorithm to find a root of a single general nonlinear equation:

$$
f(x)=0
$$

All algorithms for this kind of problem are iterative:

- Start with an initial guess $x_{0}$
- Compute a sequence of iterates $\left\{x_{k}\right\}$
- Hope (or prove) that $x_{k} \rightarrow x$ where $x$ is a root of $f($.$) .$

From here on: Consider only time-independent problems.

## Approach to nonlinear problems

Goal: Find a "fixed point" $x$ so that

$$
f(x)=0
$$

Choose a function $g(x)$ so that the solutions of

$$
x=g(x)
$$

are also roots of $f(x)$. Then iterate

$$
x_{k+1}=g\left(x_{k}\right)
$$

This iteration converges if $g$ is a contraction.

## Approach to nonlinear problems

Goal: Choose $g(x)$ so that

$$
x=g(x) \quad \Leftrightarrow \quad f(x)=0
$$

## Examples:

- "Picard iteration" (assume that $f(x)=p(x) x-h)$ :

$$
g(x)=\frac{1}{p(x)}^{h} \quad \rightarrow \quad p\left(x_{k}\right) x_{k+1}=h
$$

- Pseudo-timestepping:

$$
g(x)=x \pm \Delta \tau f(x) \quad \rightarrow \quad \frac{x_{k+1}-x_{k}}{\Delta \tau}= \pm f\left(x_{k}\right)
$$

- Newton's method

$$
g(x)=x-\frac{f(x)}{f^{\prime}(x)} \quad \rightarrow \quad x_{k+1}=x_{k}-\frac{f\left(x_{k}\right)}{f^{\prime}\left(x_{k}\right)}
$$

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Picard iteration: Repeatedly solve

$$
-\nabla \cdot\left(A \frac{\nabla u_{k+1}}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}}\right)=f
$$

or in weak form:

$$
\left(\nabla \phi, \frac{A}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}} \nabla u_{k+1}\right)=(\phi, f) \quad \forall \phi \in H_{0}^{1}
$$

This is a linear PDE in $u_{k+1}$. We know how to do this.

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Picard iteration: Repeatedly solve

$$
\left(\nabla \phi, \frac{A}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}} \nabla u_{k+1}\right)=(\phi, f) \quad \forall \phi \in H_{0}^{1}
$$

## Pros and cons:

- This is like the Poisson equation with a spatially varying coefficient (like step-6) $\rightarrow$ SPD matrix, easy
- Converges frequently
- Picard iteration typically converges rather slowly


## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Pseudo-timestepping: Iterate to $\tau \rightarrow \infty$ the equation

$$
\frac{\partial u(\tau)}{\partial \tau}-\nabla \cdot\left(A \frac{\nabla u(\tau)}{\sqrt{1+|\nabla u(\tau)|^{2}}}\right)=f
$$

For example using the explicit Euler method:

$$
\frac{u_{k+1}-u_{k}}{\Delta \tau}-\nabla \cdot\left(A \frac{\nabla u_{k}}{\sqrt{1+\left|\nabla u_{k}\right|}}\right)=f
$$

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Pseudo-timestepping: Iterate to $\tau \rightarrow \infty$ the equation

$$
\frac{\partial u(\tau)}{\partial \tau}-\nabla \cdot\left(A \frac{\nabla u(\tau)}{\sqrt{1+|\nabla u(\tau)|^{2}}}\right)=f
$$

Alternatively (and better): Semi-implicit Euler method...

$$
\frac{u_{k+1}-u_{k}}{\Delta \tau}-\nabla \cdot\left(A \frac{\nabla u_{k+1}}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}}\right)=f
$$

...or some higher order time stepping method.

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Pseudo-timestepping: Semi-implicit Euler method

$$
\frac{u_{k+1}-u_{k}}{\Delta \tau}-\nabla \cdot\left(A \frac{\nabla u_{k+1}}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}}\right)=f
$$

Pros and cons:

- Pseudo-timestepping converges almost always
- Easy to implement (it's just a heat equation)
- With implicit method, can make time step larger+larger
- Often takes many many time steps


## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Newton's method: Consider the residual

$$
R(u)=f+\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)
$$

Solve $R(u)=0$ by using the iteration

$$
u_{k+1}=u_{k}-\left[R^{\prime}\left(u_{k}\right)\right]^{-1} R\left(u_{k}\right)
$$

or equivalently:

$$
\left[R^{\prime}\left(u_{k}\right)\right] \delta u_{k}=-R\left(u_{k}\right), \quad u_{k+1}=u_{k}+\delta u_{k}
$$

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Newton's method: Iterate on

$$
\left[R^{\prime}\left(u_{k}\right)\right] \delta u_{k}=-R\left(u_{k}\right), \quad u_{k+1}=u_{k}+\delta u_{k}
$$

Here, this means:

$$
-\nabla \cdot\left(\frac{A}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}} \nabla \delta u_{k}\right)+\nabla \cdot\left(A \frac{\nabla u_{k} \cdot \nabla \delta u_{k}}{\left(1+\left|\nabla u_{k}\right|^{k}\right)^{/ 2 / 2}} \nabla u_{k}\right)=f+\nabla \cdot\left(\frac{A}{\sqrt{1+\left|\nabla u_{k}\right|^{2}}} \nabla u_{k}\right)
$$

This is in fact a symmetric and positive definite problem.

## Application to the minimal surface equation

Goal: Solve

$$
-\nabla \cdot\left(A \frac{\nabla u}{\sqrt{1+|\nabla u|^{2}}}\right)=f
$$

Newton's method: Iterate on

$$
\left[R^{\prime}\left(u_{k}\right)\right] \delta u_{k}=-R\left(u_{k}\right), \quad u_{k+1}=u_{k}+\delta u_{k}
$$

## Pros and cons:

- Rapid, quadratic convergence
- Only converges when started close enough to the solution
- Operator has different structure than in Picard


## Summary for nonlinear problems

- Nonlinear (stationary) PDEs are difficult because there are no direct algorithms for nonlinear systems of equations
- In the context of PDEs, we typically use one of three classes of methods:
- Picard iteration
. converges frequently, but slowly
- Pseudo-timestepping
. converges most reliably, but slowly
- Newton iteration
. does not always converge
. if it converges, then very rapidly


## MATH 676

## Finite element methods in scientific computing

Wolfgang Bangerth, Texas A\&M University

