

# A convergent evolving finite element algorithm for mean curvature flow of closed surfaces

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joint work with

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# Mean curvature flow

Surface evolution under **mean curvature flow** (MCF):

$$v = -H\nu_{\Gamma(t)}.$$

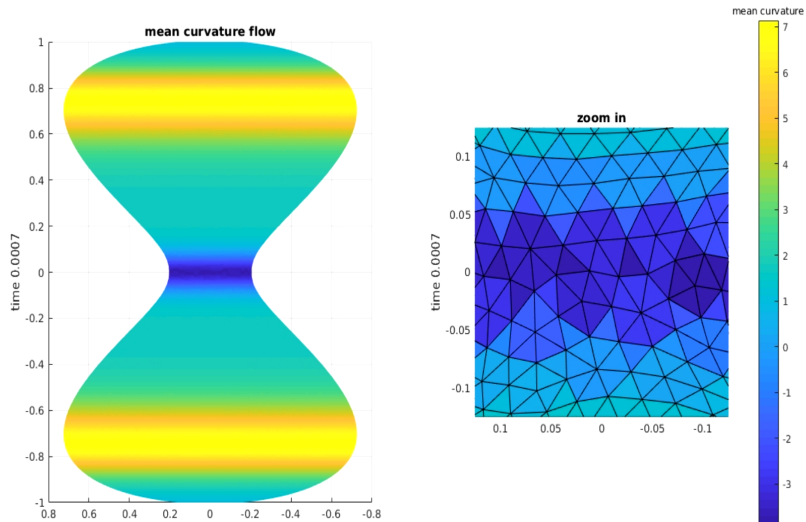
Some references:

- [Huisken (1984)] – analysis;
- appears in many biological and physical models.

Some **finite element** literature:

- [Dziuk (1990)] – first algorithm for mean curvature flow;
- [Barrett, Garcke and Nürnberg] – many schemes, with good properties;  
Both without error analysis.
- for curves or graphs much more is known due to Barrett, Deckelnick, Dziuk, Pozzi, Stinner, Styles, and many others...

# An example for MCF



# Outline

- Notations, coupled system and weak form
- Evolving surface finite elements and matrix–vector formalism
- Time integration
  - Relating different surfaces
  - Stability via energy estimates
- Numerical experiments

Notations, coupled system and weak form

## Evolving surfaces

Let  $\Gamma(t) \subset \mathbb{R}^3$  be a closed surface

$$\Gamma[X] = \Gamma(t) = \Gamma[X(\cdot, t)] = \{X(p, t) : p \in \Gamma^0\},$$

where  $\Gamma^0$  is an initial surface, and

$$X : \Gamma^0 \times [0, T] \rightarrow \mathbb{R}^3 \text{ a smooth vector-field.}$$

Consider a point  $p \in \Gamma^0$  fixed, the **surface velocity**  $v$  satisfies, in  $x(t) = X(p, t)$ , by

$$\partial_t x(t) = v(x(t), t) \quad (= \partial_t X(p, t)).$$

The position  $x = X(p, t)$  is obtained by solving the above ODE from 0 to  $t$  for a fixed  $p$ ,  $\Gamma[X(\cdot, t)]$  is a collection of such points  $x$ .

# Differential operators on $\Gamma$

- Normal vector:  $\nu_\Gamma$
- Tangential gradient:  $\nabla_\Gamma u = \nabla u - (\nabla u \cdot \nu_\Gamma)\nu_\Gamma : \Gamma \rightarrow \mathbb{R}^3$
- Laplace–Beltrami operator:  $\Delta_\Gamma u = \nabla_\Gamma \cdot \nabla_\Gamma u$   
(for  $u : \Gamma \rightarrow \mathbb{R}$ , on a regular surface  $\Gamma \subset \mathbb{R}^3$ )

## Geometric quantities and mean curvature $H$

- extended Weingarten map ( $3 \times 3$  symmetric matrix)

$$A(x) = \nabla_{\Gamma} \nu_{\Gamma}(x)$$

- with eigenvalues:  $\kappa_1$  and  $\kappa_2$ , the principal curvatures, and 0 (with eigenvector  $\nu_{\Gamma}$ )
- they define

mean curvature  $H = \text{tr}(A) = \kappa_1 + \kappa_2,$

$$|A|^2 = \|A\|_F^2 = \kappa_1^2 + \kappa_2^2.$$



## MCF and Dziuk's algorithm

A regular surface  $\Gamma[X]$  moving under **mean curvature flow** satisfies:

$$\begin{aligned}\partial_t X &= v, \\ v &= -H\nu_{\Gamma[X]}.\end{aligned}$$

Heat like equation, using that  $-H\nu_{\Gamma} = \Delta_{\Gamma} X_{\Gamma}$ :

$$\partial_t X(p, t) = \Delta_{\Gamma[X]} X_{\Gamma[X]}.$$

The algorithm [Dziuk (1990)] is based on its weak formulation, for all test functions  $\varphi \in H^1(\Gamma[X])^3$ :

$$\int_{\Gamma[X]} v \cdot \varphi = - \int_{\Gamma[X]} \nabla_{\Gamma[X]} X_{\Gamma[X]} \cdot \nabla_{\Gamma[X]} \varphi.$$

+ ODE for positions.

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Simple and elegant algorithm but, unfortunately, **no** convergence result.

## The analysts approach

A regular surface  $\Gamma[X]$  moving under mean curvature flow satisfies:

$$\begin{aligned}\partial_t X &= v, \\ v &= -H\nu_{\Gamma[X]}.\end{aligned}$$

Lemma [Huisken (1984)]

For a regular surface  $\Gamma[X]$  moving under mean curvature flow, the normal vector and the mean curvature satisfy

$$\begin{aligned}\partial^\bullet \nu &= \Delta_{\Gamma[X]} \nu + |A|^2 \nu, \\ \partial^\bullet H &= \Delta_{\Gamma[X]} H + |A|^2 H.\end{aligned}$$

---

**Coupled system: fundamental for analysis,  
but were not used for numerics.**

## Weak form

The numerical discretization is based on a weak formulation:

$$\begin{aligned} & \int_{\Gamma[X]} \nabla_{\Gamma[X]} \boldsymbol{\nu} \cdot \nabla_{\Gamma[X]} \varphi^{\nu} + \int_{\Gamma[X]} \boldsymbol{\nu} \cdot \varphi^{\nu} \\ & \quad = - \int_{\Gamma[X]} \nabla_{\Gamma[X]} (H \boldsymbol{\nu}) \cdot \nabla_{\Gamma[X]} \varphi^{\nu} - \int_{\Gamma[X]} H \boldsymbol{\nu} \cdot \varphi^{\nu}, \\ & \int_{\Gamma[X]} \partial^{\bullet} \boldsymbol{\nu} \cdot \varphi^{\nu} + \int_{\Gamma[X]} \nabla_{\Gamma[X]} \boldsymbol{\nu} \cdot \nabla_{\Gamma[X]} \varphi^{\nu} = \int_{\Gamma[X]} |\nabla_{\Gamma[X]} \boldsymbol{\nu}|^2 \boldsymbol{\nu} \cdot \varphi^{\nu}, \\ & \int_{\Gamma[X]} \partial^{\bullet} H \varphi^H + \int_{\Gamma[X]} \nabla_{\Gamma[X]} H \cdot \nabla_{\Gamma[X]} \varphi^H = \int_{\Gamma[X]} |\nabla_{\Gamma[X]} \boldsymbol{\nu}|^2 H \varphi^H, \end{aligned}$$

+ ODE for positions.

# Evolving surface finite elements and matrix–vector formulation

## ESFEM – basic notations

- We collect the evolving nodes into the vector  $\mathbf{x}(t) \in \mathbb{R}^{3N}$ .
- The nodes  $\mathbf{x}(t) \in \mathbb{R}^{3N}$  determine the approximation

$$\Gamma[X(\cdot, t)] \approx \Gamma[\mathbf{x}(t)].$$

- Nodal basis functions, of degree  $k$ ,  $\phi_j[\mathbf{x}]$  span the evolving finite element space  $S_h(\mathbf{x})$  on  $\Gamma_h[\mathbf{x}]$ .

## Spatial semi-discretisation – Dziuk's algorithm

Find the nodal vector  $\mathbf{x}(t) \in \mathbb{R}^{3N}$  and discrete velocity  $\mathbf{v}_h(\cdot, t) \in \mathcal{S}_h(\mathbf{x}(t))^3$  such that

$$\int_{\Gamma_h[\mathbf{x}]} \mathbf{v}_h \cdot \varphi_h = - \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} \mathbf{x}_{\Gamma_h[\mathbf{x}]} \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h,$$
$$\partial_t \mathbf{X}_h = \mathbf{v}_h,$$

for all  $\varphi_h(\cdot, t) \in \mathcal{S}_h(\mathbf{x}(t))^3$ , with  $\mathbf{X}_h(\cdot, t) = \sum_{j=1}^N x_j(t) \phi_j[\mathbf{x}(0)]$ .

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Matrix–vector formulation:

The mass and stiffness matrices are denoted by  $\mathbf{M}(\mathbf{x})$  and  $\mathbf{A}(\mathbf{x})$

$$\mathbf{M}(\mathbf{x})\mathbf{v} + \mathbf{A}(\mathbf{x})\mathbf{x} = 0,$$
$$\dot{\mathbf{x}} = \mathbf{v}.$$

## Spatial semi-discretisation – Dziuk's algorithm

Find the nodal vector  $\mathbf{x}(t) \in \mathbb{R}^{3N}$  and discrete velocity  $v_h(\cdot, t) \in S_h(\mathbf{x}(t))^3$  such that

$$\int_{\Gamma_h[\mathbf{x}]} v_h \cdot \varphi_h = - \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} X_h[\mathbf{x}] \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h,$$
$$\partial_t X_h = v_h,$$

for all  $\varphi_h(\cdot, t) \in S_h(\mathbf{x}(t))^3$ , with  $X_h(\cdot, t) = \sum_{j=1}^N x_j(t) \phi_j[\mathbf{x}(0)]$ .

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## Spatial semi-discretisation – coupled system

Find the unknown nodal vector  $\mathbf{x}(t) \in \mathbb{R}^{3N}$  and the unknown finite element functions  $u_h(\cdot, t) \in S_h(\mathbf{x}(t))$  and  $v_h(\cdot, t) \in S_h(\mathbf{x}(t))^3$  such that, for all  $\varphi_h(\cdot, t) \in S_h(\mathbf{x}(t))$ , with  $\partial_h^\bullet \varphi_h = 0$ , and for all  $\psi_h(\cdot, t) \in S_h(\mathbf{x}(t))^3$

$$\begin{aligned} & \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} v_h \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h^\vee + \int_{\Gamma_h[\mathbf{x}]} v_h \cdot \varphi_h^\vee \\ &= - \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} (H_h \nu_h) \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h^\vee - \int_{\Gamma_h[\mathbf{x}]} H_h \nu_h \cdot \varphi_h^\vee, \\ & \int_{\Gamma_h[\mathbf{x}]} \partial_h^\bullet \nu_h \cdot \varphi_h^\vee + \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} \nu_h \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h^\vee = \int_{\Gamma_h[\mathbf{x}]} |\nabla_{\Gamma_h[\mathbf{x}]} \nu_h|^2 \nu_h \cdot \varphi_h^\vee, \\ & \int_{\Gamma_h[\mathbf{x}]} \partial_h^\bullet H_h \varphi_h^H + \int_{\Gamma_h[\mathbf{x}]} \nabla_{\Gamma_h[\mathbf{x}]} H_h \cdot \nabla_{\Gamma_h[\mathbf{x}]} \varphi_h^H = \int_{\Gamma_h[\mathbf{x}]} |\nabla_{\Gamma_h[\mathbf{x}]} \nu_h|^2 H_h \varphi_h^H, \end{aligned}$$

+ ODE for positions.



## Matrix–vector formulation

Upon setting  $\mathbf{u} = (\mathbf{n}, \mathbf{H})^T \in \mathbb{R}^{4N}$  and  $\mathbf{K}(\mathbf{x}) = \mathbf{M}(\mathbf{x}) + \mathbf{A}(\mathbf{x})$ , the semi-discrete problem is equivalent to the following differential algebraic system:

$$\begin{aligned}\mathbf{K}(\mathbf{x})\mathbf{v} &= \mathbf{g}(\mathbf{x}, \mathbf{u}), \\ \mathbf{M}(\mathbf{x})\dot{\mathbf{u}} + \mathbf{A}(\mathbf{x})\mathbf{u} &= \mathbf{f}(\mathbf{x}, \mathbf{u}), \\ \dot{\mathbf{x}} &= \mathbf{v}.\end{aligned}$$

---

As compared to [Dziuk (1990)]:

$$\begin{aligned}\mathbf{M}(\mathbf{x})\mathbf{v} + \mathbf{A}(\mathbf{x})\mathbf{x} &= 0, \\ \dot{\mathbf{x}} &= \mathbf{v}.\end{aligned}$$

Time integration:  
stability and convergence

## Linearly implicit full discretization

Recall the matrix–vector formulation:

$$\begin{aligned}\mathbf{K}(\mathbf{x})\mathbf{v} &= \mathbf{g}(\mathbf{x}, \mathbf{u}), \\ \mathbf{M}(\mathbf{x})\dot{\mathbf{u}} + \mathbf{A}(\mathbf{x})\mathbf{u} &= \mathbf{f}(\mathbf{x}, \mathbf{u}), \\ \dot{\mathbf{x}} &= \mathbf{v}.\end{aligned}$$

A non-linear coupled problem.

# Linearly implicit full discretization

Linearly implicit  $q$ -step backward difference formulae (BDF):

$$\begin{aligned}\mathbf{K}(\tilde{\mathbf{x}}^n)\mathbf{v}^n &= \mathbf{g}(\tilde{\mathbf{x}}^n, \tilde{\mathbf{u}}^n), \\ \mathbf{M}(\tilde{\mathbf{x}}^n)\dot{\mathbf{u}}^n + \mathbf{A}(\tilde{\mathbf{x}}^n)\mathbf{u}^n &= \mathbf{f}(\tilde{\mathbf{x}}^n, \tilde{\mathbf{u}}^n), \\ \dot{\mathbf{x}}^n &= \mathbf{v}^n,\end{aligned}$$

with

discrete derivative::  $\dot{\mathbf{x}}^n = \frac{1}{\tau} \sum_{j=0}^q \delta_j \mathbf{x}^{n-j}$ , and

extrapolated value:  $\tilde{\mathbf{x}}^n = \sum_{j=0}^{q-1} \gamma_j \mathbf{x}^{n-1-j}$ .

# Stability

## Relating different surfaces – I.

Let  $\mathbf{x} \in \mathbb{R}^{3N}$  and  $\mathbf{y} \in \mathbb{R}^{3N}$  be two vectors which define the surfaces  $\Gamma_h(\mathbf{x})$  and  $\Gamma_h(\mathbf{y})$ .

Intermediate surfaces:

$$\mathbf{e} = \mathbf{x} - \mathbf{y} \iff \Gamma_h^\theta = \Gamma_h(\mathbf{y} + \theta\mathbf{e}) \quad (\theta \in [0, 1]),$$

and the corresponding error:

$$\mathbf{e}_h^\theta = \sum_{j=1}^N \mathbf{e}_j \phi_j[\mathbf{y} + \theta\mathbf{e}].$$

Relating different surfaces:

$$\mathbf{w}^T (\mathbf{M}(\mathbf{x}) - \mathbf{M}(\mathbf{y})) \mathbf{z} = \int_0^1 \int_{\Gamma_h^\theta} \mathbf{w}_h^\theta (\nabla_{\Gamma_h^\theta} \cdot \mathbf{e}_h^\theta) \mathbf{z}_h^\theta \, d\theta,$$

$$\mathbf{w}^T (\mathbf{A}(\mathbf{x}) - \mathbf{A}(\mathbf{y})) \mathbf{z} = \int_0^1 \int_{\Gamma_h^\theta} \nabla_{\Gamma_h^\theta} \mathbf{w}_h^\theta \cdot (D_{\Gamma_h^\theta} \mathbf{e}_h^\theta) \nabla_{\Gamma_h^\theta} \mathbf{z}_h^\theta \, d\theta,$$

## Relating different surfaces – II.

We proved **six technical lemmas**, and **techniques** from [K., Li, Lubich and Power (2017)], which relate different evolving surfaces with one another. For example:

$$\begin{aligned}\|\mathbf{w}\|_{\mathbf{M}(\mathbf{y}+\mathbf{e})} &\leq c \|\mathbf{w}\|_{\mathbf{M}(\mathbf{y})}, \\ \|\nabla_{\Gamma_h^\theta} w_h^\theta\|_{L^p(\Gamma_h^\theta)} &\leq c_p \|\nabla_{\Gamma_h^0} w_h^0\|_{L^p(\Gamma_h^0)},\end{aligned}$$

etc. . . . , and

$$\begin{aligned}\mathbf{w}^T (\mathbf{M}(\mathbf{x}) - \mathbf{M}(\mathbf{y})) \mathbf{z} &\leq c \|\mathbf{w}\|_{\mathbf{M}(\mathbf{y})} \|\mathbf{z}\|_{\mathbf{M}(\mathbf{y})}, \\ \mathbf{w}^T (\mathbf{M}(\mathbf{x}) - \mathbf{M}(\mathbf{y})) \mathbf{w} &\leq c \|e_h^0\|_{W^{1,\infty}(\Gamma_h[\mathbf{y}])} \|\mathbf{w}\|_{\mathbf{M}(\mathbf{y})}^2,\end{aligned}$$

etc. . . .

**Under the important condition on  $\mathbf{e}$ :  $\|e_h^0\|_{W^{1,\infty}(\Gamma_h[\mathbf{y}])} \leq \frac{1}{2}$ .**

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$$\begin{aligned}\mathbf{w}^T (\mathbf{M}(\mathbf{x}) - \mathbf{M}(\mathbf{y})) \mathbf{z} &\leq c \|\mathbf{w}\|_{\mathbf{M}(\mathbf{y})} \|\mathbf{z}\|_{\mathbf{M}(\mathbf{y})}, \\ \mathbf{w}^T (\mathbf{M}(\mathbf{x}) - \mathbf{M}(\mathbf{y})) \mathbf{w} &\leq c \|e_h^0\|_{W^{1,\infty}(\Gamma_h[\mathbf{y}])} \|\mathbf{w}\|_{\mathbf{M}(\mathbf{y})}^2,\end{aligned}$$

etc. . . .

**Under the important condition on  $\mathbf{e}$ :  $\|e_h^0\|_{W^{1,\infty}(\Gamma_h[\mathbf{y}])} \leq \frac{1}{2}$ .**



**A key issue is to establish  
a pointwise bound on the  $W^{1,\infty}$  norm of the errors.**

- (i) Obtain **pointwise  $H^1$  norm** error estimates at time  $t_n$ ;
- (ii) Using an **inverse estimate** to establish bounds in the  $W^{1,\infty}$  norm;
- (iii) Repeat for  $t_{n+1}$ .

## Illustrate using a simple case

Consider (in the usual Hilbert space setting) the parabolic problem:

$$\begin{aligned}(\dot{u}(t), \varphi) + (Au(t), \varphi) &= (f(t), \varphi), \\ u(0) &= u_0.\end{aligned}$$

Energy estimates, testing with  $u$  and  $\dot{u}$ :

$$\frac{d}{dt}|u|^2 + \|u\|^2 \leq c\|f\|_*^2, \quad (\text{a})$$

$$|\dot{u}|^2 + \frac{d}{dt}\|u\|^2 \leq c|f|^2, \quad (\text{b})$$

then integrate in time.

## Energy estimates for BDF methods

Using **G-stability** of [Dahlquist (1978)] and the **multiplier techniques** of [Nevanlinna and Odeh (1981)]:

Testing with multiplier  $u^n - \eta u^{n-1}$  ( $A$ -stable:  $\eta = 0$ ,  $A(\alpha)$ -stable:  $0 < \eta < 1$ ):

$$(\dot{u}^n, u^n - \eta u^{n-1}) + (Au^n, u^n - \eta u^{n-1}) = (f^n, u^n - \eta u^{n-1}). \quad (\text{a})$$

for PDEs: [Lubich, Mansour and Venkataraman (2013)], [Akrivis and Lubich (2015)], ...

Testing with  $\dot{u}^n$ :

$$(\dot{u}^n, \dot{u}^n) + (Au^n, \dot{u}^n) = (f^n, \dot{u}^n). \quad (\text{b})$$

---

**Where is the multiplier?**

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for PDEs: [Lubich, Mansour and Venkataraman (2013)], [Akrivis and Lubich (2015)], ...

**Subtract** the equations at time  $t_{n-1}$  from at time  $t_n$ , and test with  $\dot{u}^n$ :

$$(\dot{u}^n - \eta \dot{u}^{n-1}, \dot{u}^n) + (Au^n - \eta Au^{n-1}, \dot{u}^n) = (f^n - \eta f^{n-1}, \dot{u}^n). \quad (\text{b})$$

---

**Which yields a pointwise stability estimate in the strong norm.**

## Convergence of the full discretisation

Consider the full discretisation of the **coupled mean curvature flow** problem using ESFEM of polynomial degree  $k \geq 2$  and linearly implicit BDF method with  $q \leq 5$ .

Let the solutions  $(X, v, \nu, H)$  be sufficiently smooth (i.e.  $H^{k+1}$ ).

Then for sufficiently small  $h$  and  $\tau$  satisfying (with  $C_0 > 0$  fixed arbitrary)

$$\tau^q \leq c_0 h \text{ if } q \leq 2, \text{ and } \tau \leq C_0 h \text{ if } 3 \leq q \leq 5,$$

the following estimates hold for  $0 \leq t \leq T$ :

$$\|(x_h^n)^L - \text{id}_{\Gamma(t_n)}\|_{H^1(\Gamma(t_n))} \leq C(h^k + \tau^q),$$

$$\|(v_h^n)^L - v(\cdot, t_n)\|_{H^1(\Gamma(t_n))} \leq C(h^k + \tau^q),$$

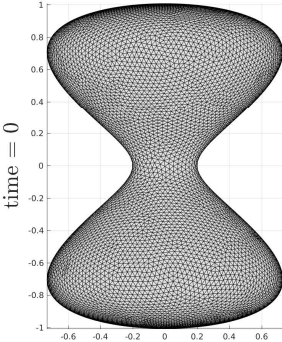
$$\|(\nu_h^n)^L - \nu(\cdot, t_n)\|_{H^1(\Gamma(t_n))} \leq C(h^k + \tau^q),$$

$$\|(H_h^n)^L - H(\cdot, t_n)\|_{H^1(\Gamma(t_n))} \leq C(h^k + \tau^q).$$

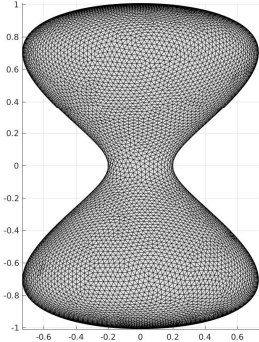
## Numerical experiments

# Comparison

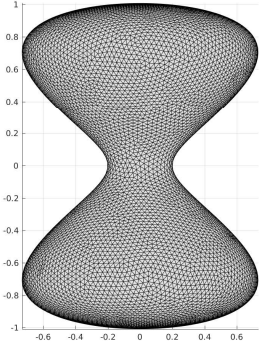
Dziuk's algorithm



$X_h$

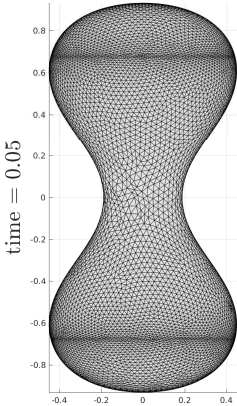


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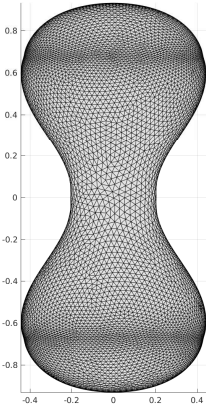


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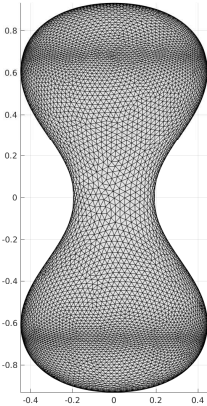
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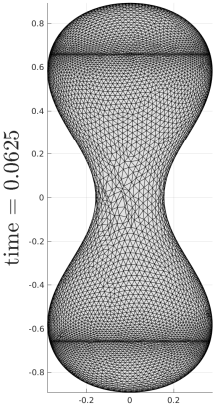
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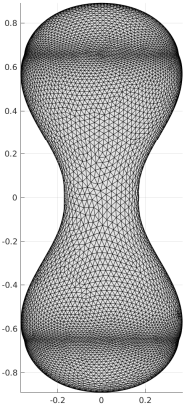


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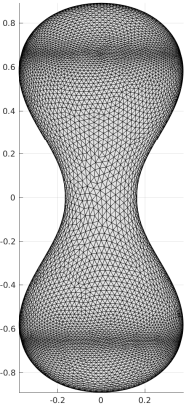
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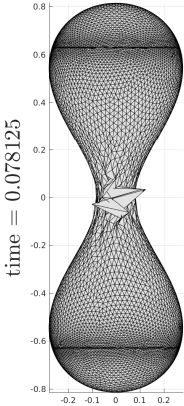


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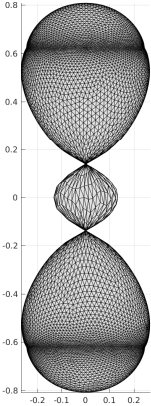


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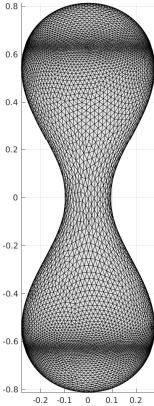
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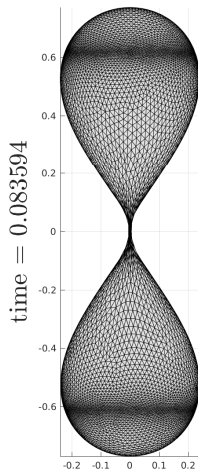
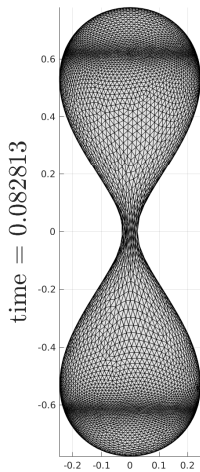
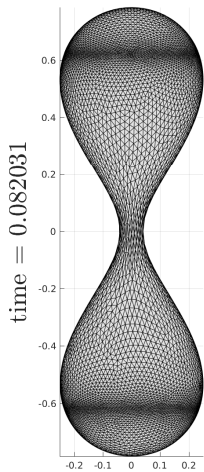
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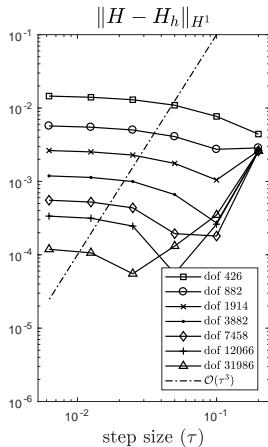
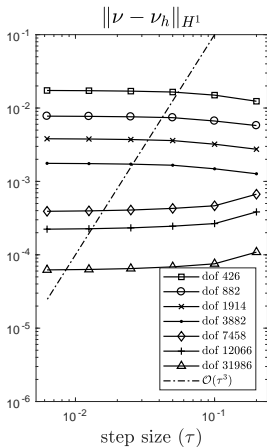
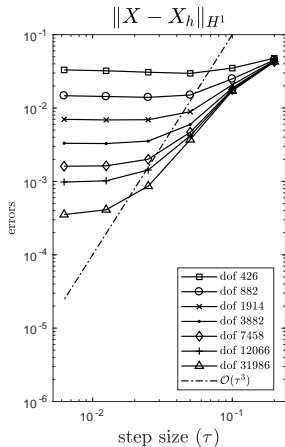
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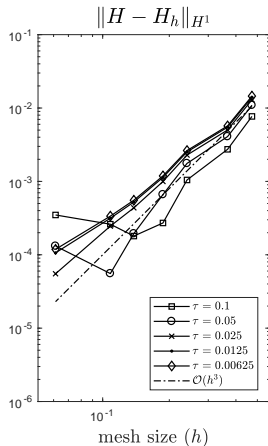
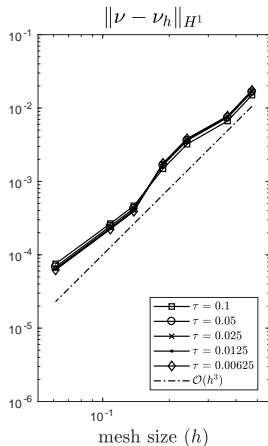
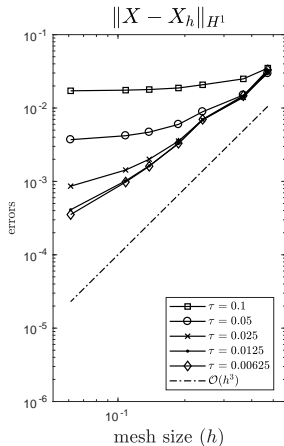
# The normalised algorithm – singularity



# Convergence – in time



# Convergence – in space



Thank you for your attention!