

## Natural Discretization of Gradient Flows

Applications to Viscous Thin Films  
and to Willmore Flow

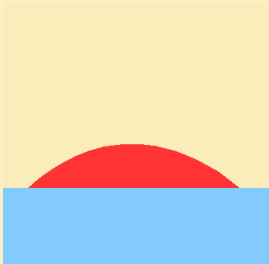
Martin Rumpf, Universität Bonn

*EPSRC Symposium*  
*New Directions in Computational PDE*  
**Warwick, January 12<sup>th</sup> – 16<sup>th</sup>**

joint work with

- thin film flow: Orestis Vantzios
- Willmore flow: Nadine Olischläger

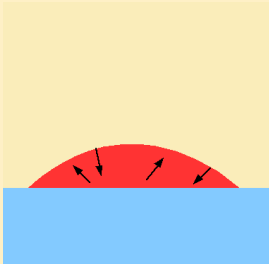
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## Application: viscous thin films

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- surface tension.

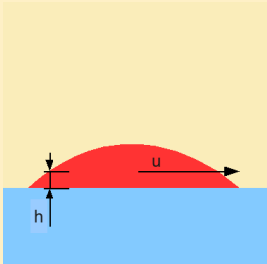


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The evolution of the thin film is described by

- the height of the film  $h$ ,
- the velocity field of the fluid  $u$ .



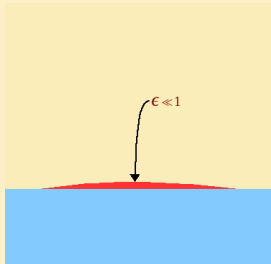
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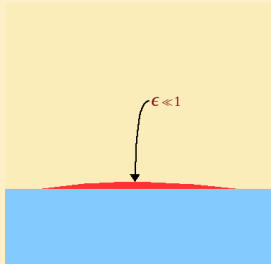
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- the height of the film  $h$ ,
- the velocity field of the fluid  $u$ .

The thickness of the film is small  $\epsilon \ll 1$ .

governing PDE [Oron, Davis, Bankoff '97]:

$$\partial_t h = - \operatorname{div} \left( \frac{h^3}{3\mu} \nabla \operatorname{div} (\sigma \nabla h) \right)$$

gradient flow perspective:

**energy** (surface tension):

$$e[h] = \int_{\Omega} \sigma \left( 1 + \frac{|\nabla h|^2}{2} \right) dx$$



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**metric:**

$$g_h(\delta h, \delta h) = g_h(u, u) = \int_{\Omega} \frac{3\mu}{h} |u|^2 dx$$

derived as lubrication limit of dissipation based on friction:

$$\int_{\text{vol}} \mu |D_y \mathbf{u} + D_y \mathbf{u}^T|^2 dy \quad , \quad y = (x, x^\perp) \quad , \quad u = \frac{1}{h} \int_0^h \mathbf{u} dx^\perp$$

**transport equation** coupling  $\delta h$  and  $u$ :

$$\delta h + \text{div}(hu) = 0$$

Given energy and metric on the manifold (cf. [Giacomelli, Otto '03]):

$$\mathcal{M} = \left\{ h : \int_{\Omega} h \, dx = \text{const} \right\} \quad \left( T_h \mathcal{M} = \left\{ \delta h : \int_{\Omega} \delta h \, dx = 0 \right\} \right)$$

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$$\Rightarrow \mathbf{g}_h(\partial_t h, \theta) = -e'[h](\theta)$$

[GF]  $\Rightarrow$  [PDE]:

$$0 = \mathbf{g}_h(\partial_t h, \delta h) + e'[h](\delta h)$$

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We consider a compact surface  $\mathcal{S} = \mathcal{S}[x]$  embedded in  $\mathbb{R}^n$  ( $n = 2, 3$ ) and the **energy**:

$$w[x] = \frac{1}{2} \int_{\mathcal{S}} h^2 \, da$$

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Then, **Willmore flow** is the corresponding gradient flow (GF):

$$\partial_t x = -\text{grad}_g w[x]$$

governing PDE ( $n = 3$ ):

$$\partial_t x = \left( \Delta_S h + h \left( |D_S n|^2 - \frac{h^2}{2} \right) \right) n$$

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**Remark:** There is an inner variational principle, i.e.

$$h = \text{grad}_S a[x], \quad \text{where } a[x] = \int_S da$$

**Numerical approaches:**

[Rusu '01], [Meyer, Simonett '02], [Grzibovski, Heintz '03], [Droske, M. '04],  
[Bobenko, Schröder '05], [Dziuk, Deckelnick '06], [Barrett, Garcke, Nürnberg  
'08], [Dziuk '08] ...

■ For the gradient flow  $\dot{x} = \text{grad}_g e[x]$  on a manifold  $\mathcal{M}$  and given  $x^0$  define time discrete solutions  $(x^k)_{k=0, \dots}$  ( $x_k \approx x(k\tau)$ ):

■

$$x^{k+1} = \arg \min_{x \in \mathcal{M}} \frac{1}{2\tau} \text{dist}(x, x^k)^2 + e[x]$$



## Natural time discretization of gradient flows

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energy estimate as a direct consequence:

$$e[x^{k+1}] + \frac{1}{2\tau} \text{dist}(x^{k+1}, x^k)^2 \leq 0 + e[x^k]$$

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**Generalization to the heat equation:**

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Given  $h^0$  define time discrete solutions  $(h^k)_{k=0,\dots}$ :

$$h^{k+1} = \arg \min_h \frac{1}{2\tau} \text{dist}(h, h^k)^2 + e[h]$$



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## Natural time discretization of thin film flow

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→ PDE constraint optimization problem

$$u^{k+1} = \arg \min_u \frac{\tau}{2} \inf_{\gamma} \left( \int_0^1 \sqrt{g_h(u(t_k + \tau s), u(t_k + \tau s))} \, ds \right)^2 + e[h[u, h^k]],$$

where  $\partial_t h + \operatorname{div}(h u) = 0$ ,

$$h(t_k) = h^k, h(t_{k+1}) = h^{k+1}$$

Approximation by numerical quadrature in the general case:

$$\text{dist}(x, x^k)^2 = \inf_{\gamma} \left( \int_0^1 \sqrt{g_{\gamma(s)}(\dot{\gamma}(s), \dot{\gamma}(s))} \, ds \right)^2$$

Approximation by numerical quadrature in the general case:

$$\begin{aligned} \text{dist}(x, x^k)^2 &= \inf_{\gamma} \left( \int_0^1 \sqrt{g_{\gamma(s)}(\dot{\gamma}(s), \dot{\gamma}(s))} \, ds \right)^2 \\ &\approx g_{\gamma(r)}(\dot{\gamma}(s), \dot{\gamma}(s)) \end{aligned}$$

for some  $r \in [0, 1]$

numerical time discretization ( $r = 1$ )

$$u^{k+1} = \arg \min_u \frac{\tau}{2} g_{h^k}(u, u) + e[h[u, h^k]]$$

space discretization:

- implicit Finite Volume scheme for the transport  
( $H^k, U^k \in \mathbb{R}^{\#\text{dofs}}$ ):

$$L(U)H(U, H^k) = H^k$$

(constraint equation)

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- discrete constraint variational problem in each time step:

$$U^{k+1} = \arg \min_{U \in \mathbb{R}^{\#\text{dofs}}} \frac{\tau}{2} G_{H^k}(U, U) + E(H(U, H^k)),$$

where  $G(\cdot, \cdot)$ ,  $E(\cdot)$  are numerical quadrature evaluation corresponding to  $g(\cdot, \cdot)$  and  $e(\cdot)$ .

[Dohmen, Grunewald, Otto, R. '06],

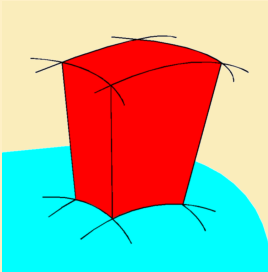
cf. also [Zhornitskaya, Bertozzi '00], [Grün, R. '00]



We can not use the transport PDE

$$\partial_t h + \operatorname{div}_{\mathcal{S}}(h \mathbf{u}) = 0$$

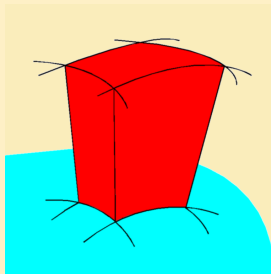
The height  $h$  is not even conserved anymore!



The correct transport PDE is

$$\partial_t \eta + \operatorname{div}_S(\eta \mathbf{u}) = 0$$

where  $\eta$  is the **fluid mass per unit surface**



$$\begin{aligned} \eta &= \int_0^h (1 - \epsilon \xi \kappa_1)(1 - \epsilon \xi \kappa_2) d\xi \\ &= h + \frac{1}{2} \mathbf{h} h^2 \epsilon + \frac{1}{3} \mathbf{k} h^3 \epsilon^2 \end{aligned}$$

## Thin film model in case of curved surface

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and  $\mathbf{u}$  is the **transport velocity**

$$\mathbf{u} = \frac{1}{\eta} \int_0^h (1 - \epsilon \xi \kappa_2) \mathbf{u}_1 + (1 - \epsilon \xi \kappa_1) \mathbf{u}_2 d\xi$$

■  
■  
■ Gradient flow perspective

■ **transport equation** (PDE constraint)

$$\delta\eta + \operatorname{div}_{\mathcal{S}}(\eta\mathbf{u}) = 0$$

## Thin film model in case of curved surface (cont.)

Gradient flow perspective

**transport equation** (PDE constraint)

$$\delta\eta + \operatorname{div}_S(\eta\mathbf{u}) = 0$$

**surface energy**

$$e(h) = \int_S \sigma \left( \mathbf{h}h + \mathbf{k}h^2\epsilon + \frac{\epsilon}{2} |\nabla_S h|^2 \right)$$

## Thin film model in case of curved surface (cont.)

Gradient flow perspective

**transport equation** (PDE constraint)

$$\delta\eta + \operatorname{div}_S(\eta\mathbf{u}) = 0$$

**surface and gravitational energy**

$$e(\eta) = \int_S (\rho g z + \sigma \mathbf{h}) \eta + \frac{\epsilon}{2} \left( (\rho g \cos \theta - \sigma(\mathbf{h}^2 - 2\mathbf{k})) \eta^2 + \sigma |\nabla_S \eta|^2 \right)$$

## Gradient flow perspective

**transport equation** (PDE constraint)

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**metric** (dissipation rate)

$$g_\eta(\mathbf{u}, \mathbf{u}) = \int_S \frac{3\mu}{\eta} \mathbf{u} \cdot \left( \mathbb{I} + \epsilon \frac{\eta}{2} (\mathbf{h}\mathbb{I} + D_S n) \right) \mathbf{u}$$

## Thin film model in case of curved surface (cont.)

Minimizing the Rayleigh functional, like in the planar case, yields the PDE:

$$\partial_t \eta - \operatorname{div}_S \left\{ \frac{\eta^3}{3\mu} \left( \mathbb{I} - \epsilon \frac{\eta}{2} (\mathbf{h}\mathbb{I} + D_S n) \right) \right. \\ \left. \nabla_S (\rho g z + \sigma \mathbf{h} + \epsilon ((\rho g \cos \theta - \sigma (\mathbf{h}^2 - 2\mathbf{k}))\eta - \sigma \Delta_S \eta)) \right\} = 0$$



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- 4th order non linear PDE

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- Leading order term is **hyperbolic**, the correction is parabolic

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- Leading order term is hyperbolic, the correction is parabolic
- Mixture of transport, 2nd and 4th order diffusion terms

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- 4th order non linear PDE
- Leading order term is hyperbolic, the correction is parabolic
- Mixture of transport, 2nd and 4th order diffusion terms
- It is in agreement, up to  $O(\epsilon^2)$ , to the thin film equation in [Roy, Roberts, Simpson '02]

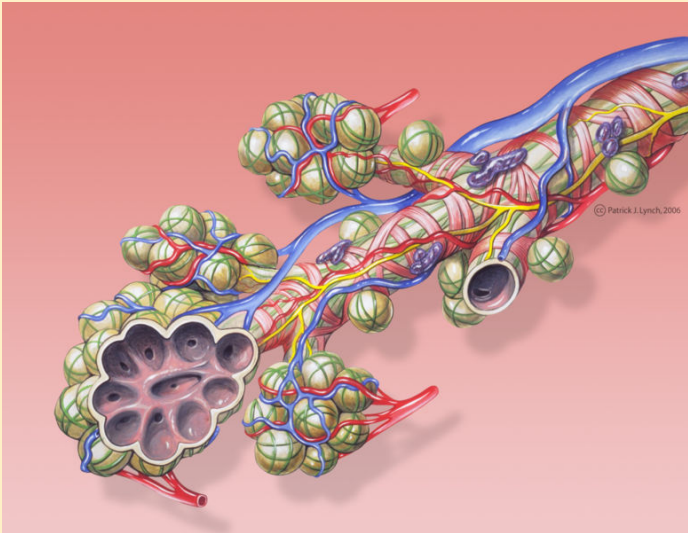
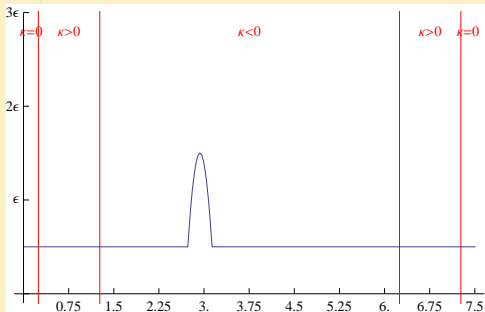
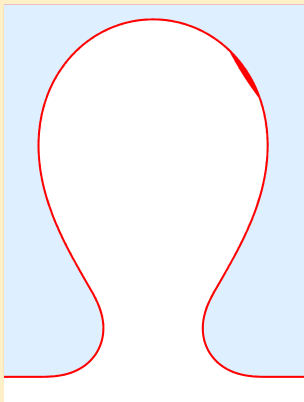


image by Patrick J. Lynch, medical illustrator; C. Carl Jaffe, MD, cardiologist

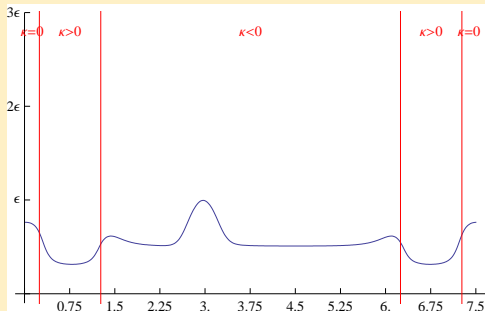
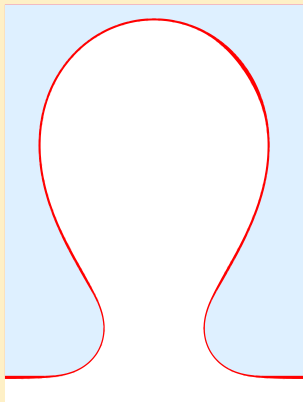
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

$$t = 0$$



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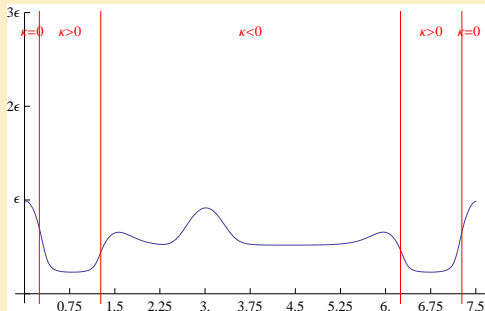
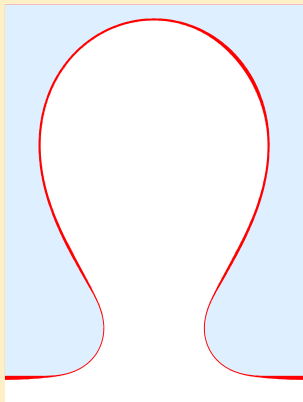
$$t = 25\tau$$





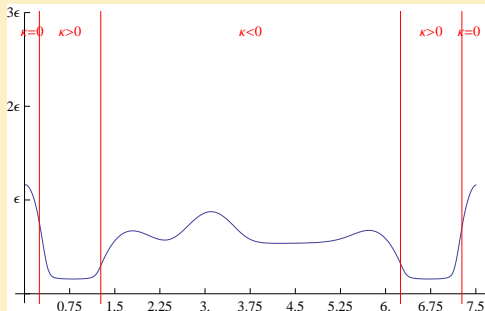
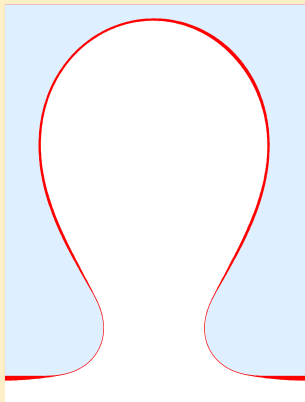
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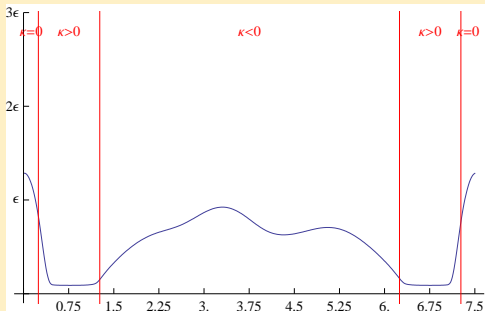
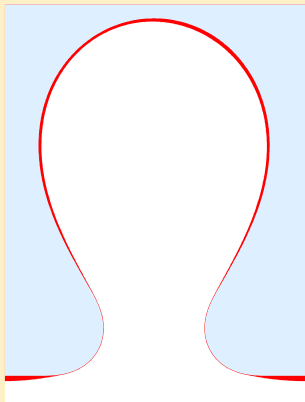
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

$$t = 100\tau$$



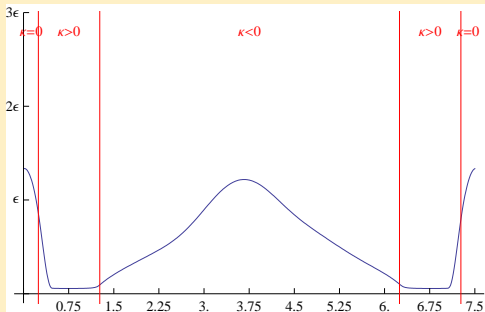
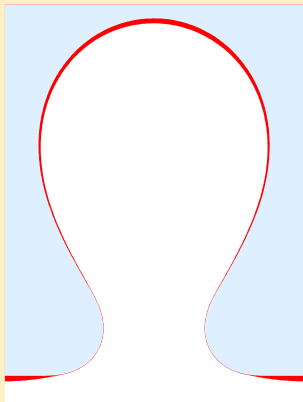
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

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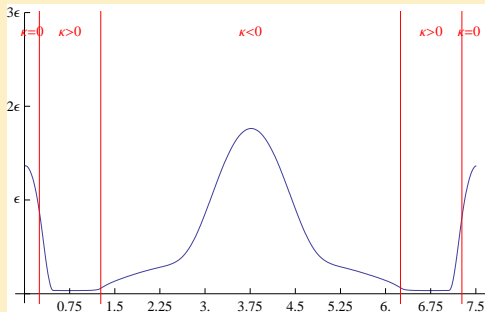
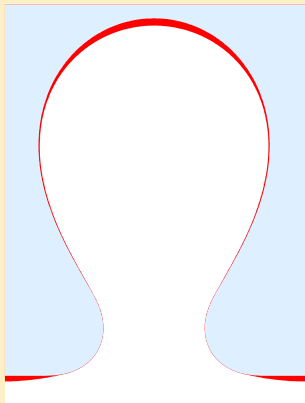
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

$$t = 500\tau$$



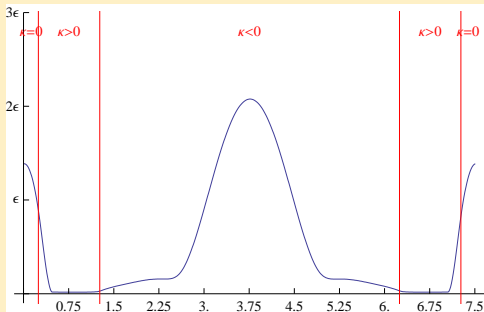
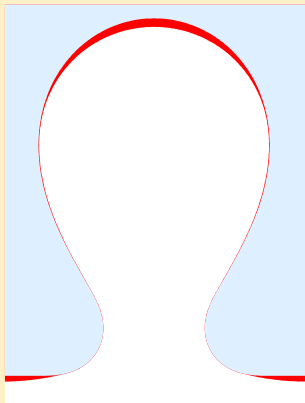
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

$$t = 1000\tau$$



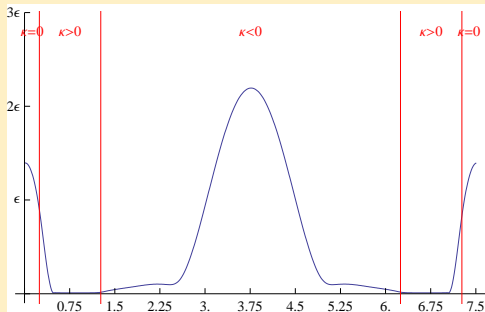
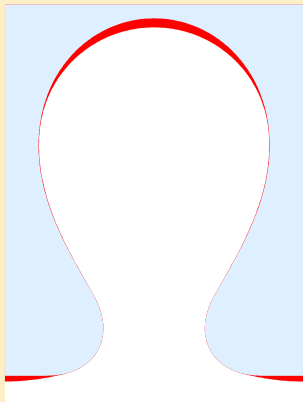
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

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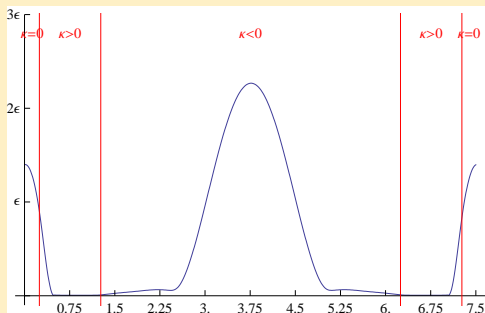
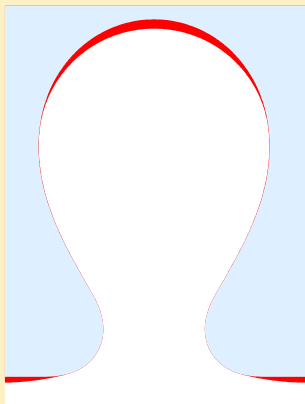
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

$$t = 5000\tau$$



liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a bump on the upper left

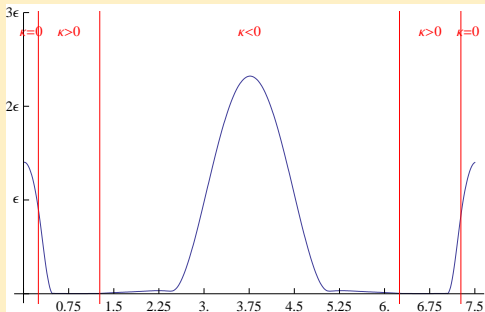
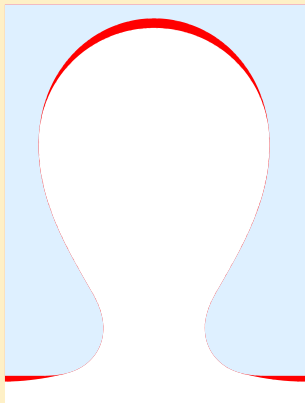
$$t = 10000\tau$$





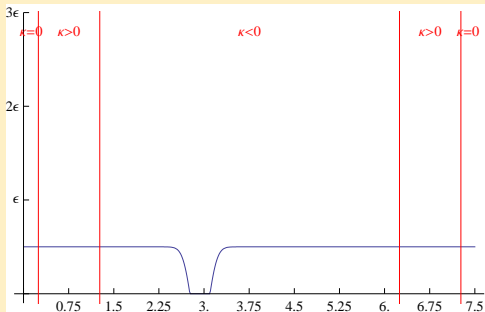
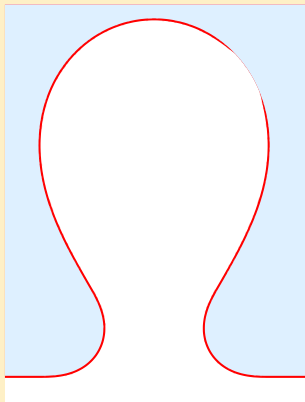
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$$t = 25000\tau$$



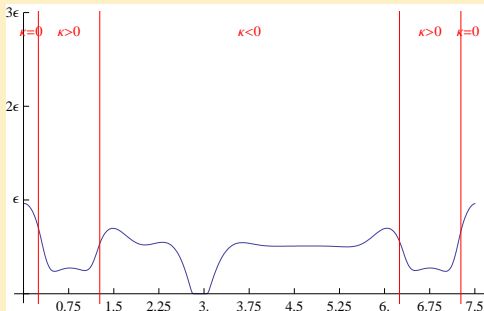
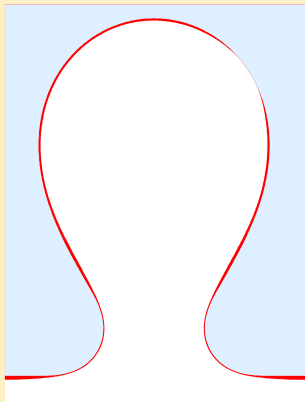
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

$$t = 0$$



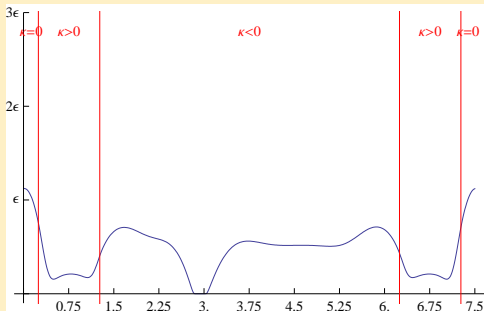
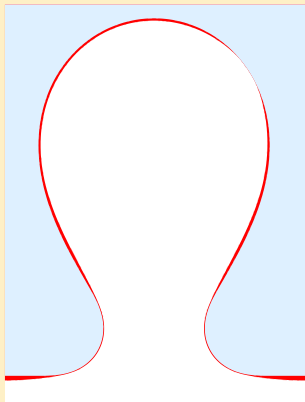
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

$$t = 25\tau$$



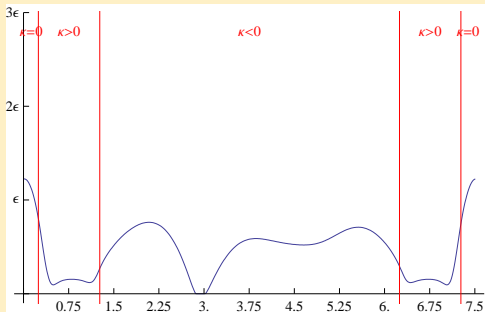
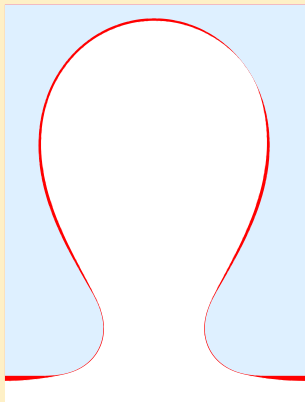
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

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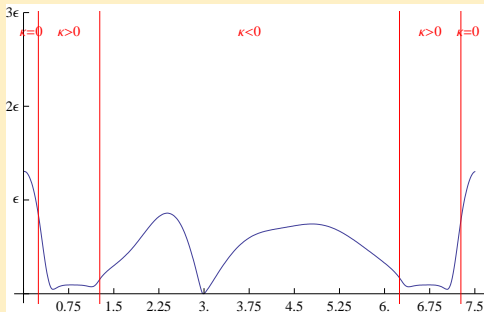
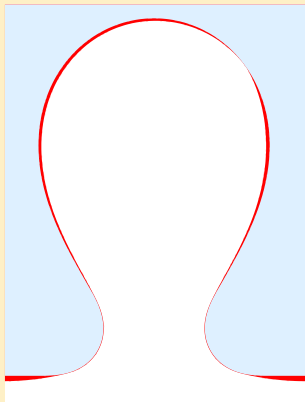
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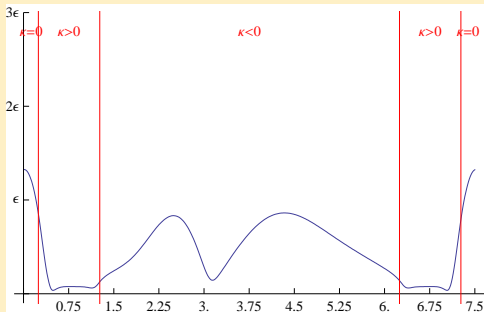
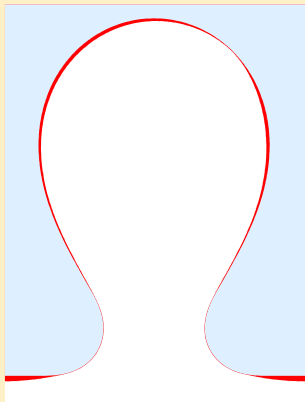
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

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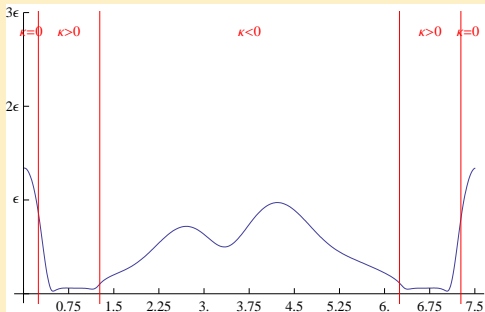
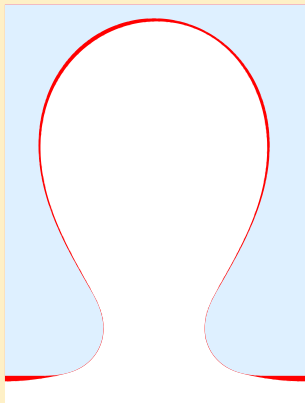
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

$$t = 350\tau$$



liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

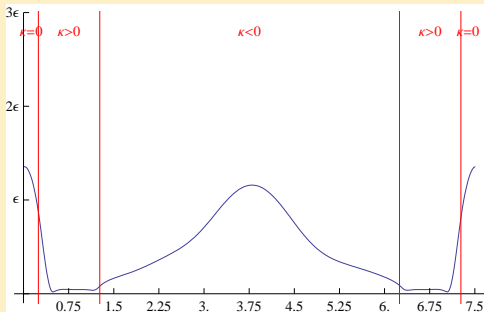
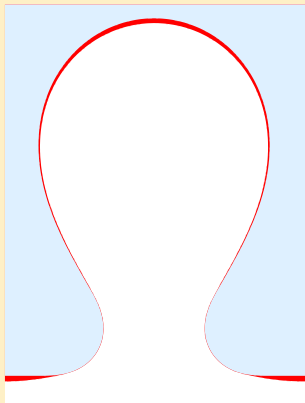
$$t = 500\tau$$





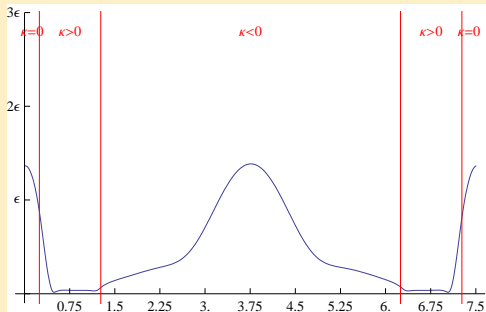
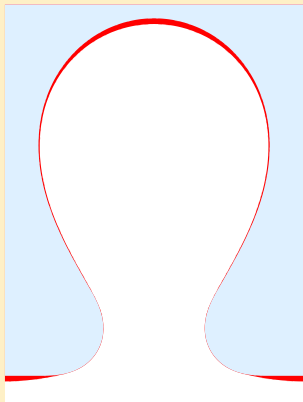
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

$$t = 7500\tau$$



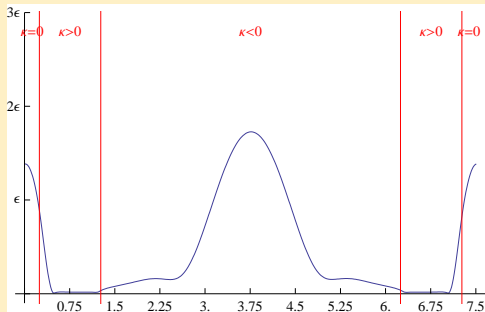
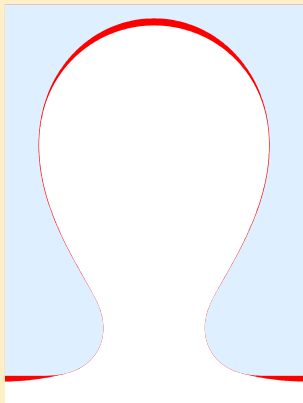
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

$$t = 1000\tau$$



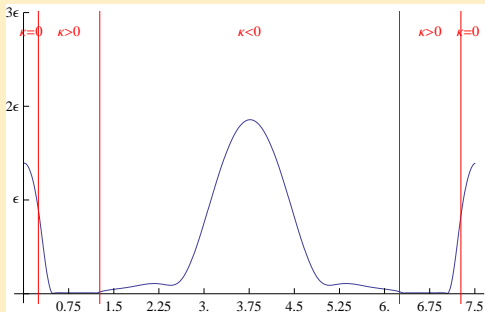
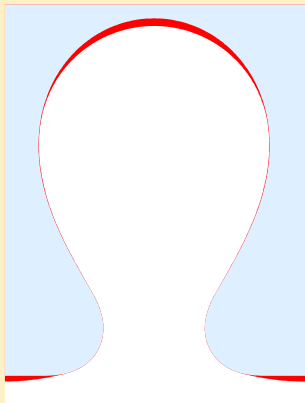
liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

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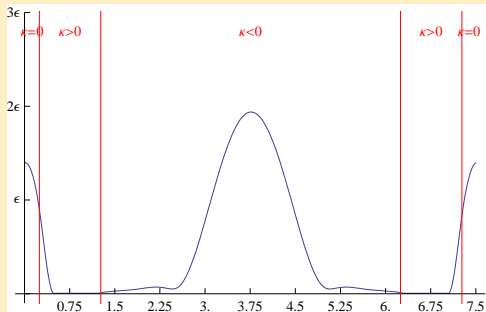
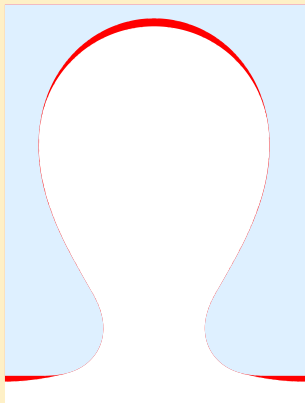
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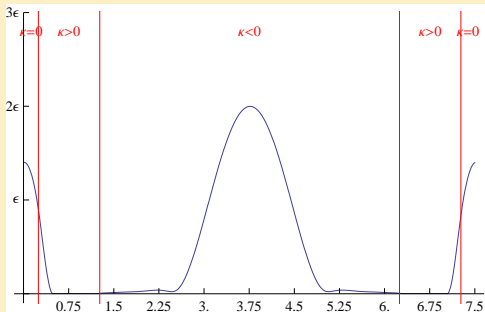
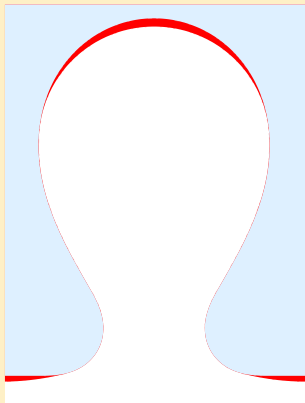
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$$t = 10000\tau$$



liquid lining ( $\epsilon = .03$ ) of alveolus-like shape with a rupture on the top left

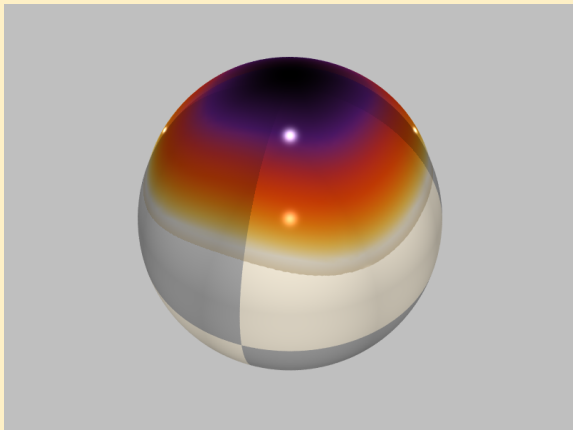
$$t = 25000\tau$$



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Four-fold symmetry perturbed droplet sliding down a sphere:



cf. [Bertozzi, Greer, Sapiro '06]



## Two step discretization of Willmore flow

Recall mean curvature motion:

$$y[x] = x^{k+1}, \quad x = x^k$$

$$y[x] = \arg \min_y \frac{1}{2\tau} \text{dist}(\mathcal{S}[y], \mathcal{S}[x])^2 + \int_{\mathcal{S}[y]} da$$

(natural gradient descent scheme)

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approximation

$$y[x] = \arg \min_y \int_{\mathcal{S}[x]} \frac{1}{2\tau} |y - x|^2 + \frac{1}{2} |\nabla_{\mathcal{S}[x]} y|^2 da$$

cf. [Dziuk '89]

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approximation of curvature vector and Willmore energy

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approximation of curvature vector and Willmore energy

$$h[x] n[x] \approx \frac{y[x] - x}{\tau}, \quad w[x] \approx \frac{1}{2} \int_{\mathcal{S}[x]} \frac{|y[x] - x|^2}{\tau^2} da$$

■ Abstract Willmore flow time step:

$$x^{k+1} = \arg \min_x \frac{1}{2\tau} \text{dist}(\mathcal{S}[x], \mathcal{S}[x^k])^2 + w[x]$$

## Two step discretization of Willmore flow (cont.)

Abstract Willmore flow time step:

$$x^{k+1} = \arg \min_x \frac{1}{2\tau} \text{dist}(\mathcal{S}[x], \mathcal{S}[x^k])^2 + w[x]$$

Based on the approximation  $w[x] \approx \frac{1}{2} \int_{\mathcal{S}[x]} \frac{|y[x]-x|^2}{\tau^2} da$  we obtain:

two step time discretization

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## Two step discretization of Willmore flow (cont.)

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where  $y[x] = \arg \min_y \int_{\mathcal{S}[x]} \frac{1}{2\tau} |y - x|^2 + \frac{1}{2} |\nabla_{\mathcal{S}[x]} y|^2 \text{d}a$

■ **Two step discretization of Willmore flow (cont.)**

$$x^{k+1} = \arg \min_x \int_{S[x^k]} |x - x^k|^2 da + \frac{1}{\tau} \int_{S[x]} |y[x] - x|^2 da$$
  
■  
■  
■  
■  
■



## Two step discretization of Willmore flow (cont.)

$$x^{k+1} = \arg \min_x \int_{S[x^k]} |x - x^k|^2 da + \frac{1}{\tau} \int_{S[x]} |y[x] - x|^2 da$$

finite element space discretization:

$X$  nodal vector

$\mathbf{M}[X]$  mass matrix  $\mathbf{M}[X]\Phi \cdot \Psi = \int_{S[X]} \Phi\Psi da$

$\mathbf{L}[X]$  stiffness matrix  $\mathbf{L}[X]\Phi \cdot \Psi = \int_{S[X]} \nabla_{S[x]}\Phi \nabla_{S[x]}\Psi da$

## Two step discretization of Willmore flow (cont.)

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**inner problem** (time discrete mean curvature)

$Y[X]$  solves  $(\mathbf{M}[X] + \tau\mathbf{L}[X])Y = \mathbf{M}[X]X$  (constraint)

## Two step discretization of Willmore flow (cont.)

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finite element space discretization:

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**inner problem** (time discrete mean curvature)

$Y[X]$  solves  $(\mathbf{M}[X] + \tau \mathbf{L}[X])Y = \mathbf{M}[X]X$  (constraint)

**outer problem** (time discrete Willmore flow)

$$X^{k+1} = \arg \min_X (\mathbf{M}[X^k](X - X^k) \cdot (X - X^k) + \tau^{-1} \mathbf{M}[X](Y[X] - X) \cdot (Y[X] - X))$$

- Circles expand according the ODE

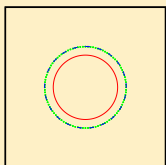
$$\dot{R}(t) = \frac{1}{2}R(t)^{-3}$$

for the radius  $R(t)$ .

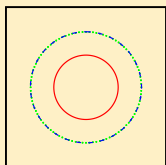
- Discrete two step radii  $R^{k+1} \approx R((k+1)\tau)$  are solutions of

$$\frac{R - R_k}{\tau} = \frac{1}{2} \frac{R^4 - 3R^2\tau}{(R^2 + \tau)^3 R_k},$$

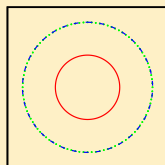
Fully discrete numerical simulation ( $\tau = \Delta x$ ):



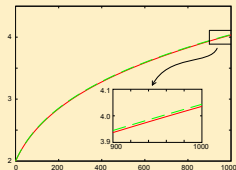
$t = 100\tau$



$t = 500\tau$



$t = 1000\tau$



$x_0(s) = (\cos(s), 4 \sin(s))$  for  $s \in [0, 2\pi]$  as initial parametrization.

modified functional:  $w[x] + \lambda a[x]$



$t = 0.0$



$t = 2.25$



$t = 4.75$



$t = 9.75$

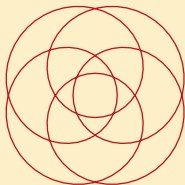
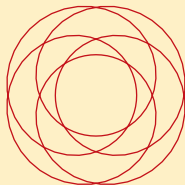
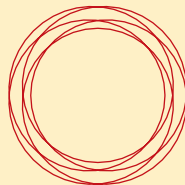
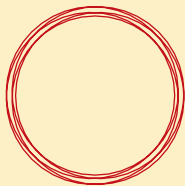
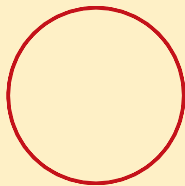
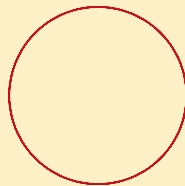


$t = 24.75$

$[n = 2, N = 100, \tau = \Delta x = 0.0632847, \lambda = 0.025.]$

## Evolution of a planar hypocycloid

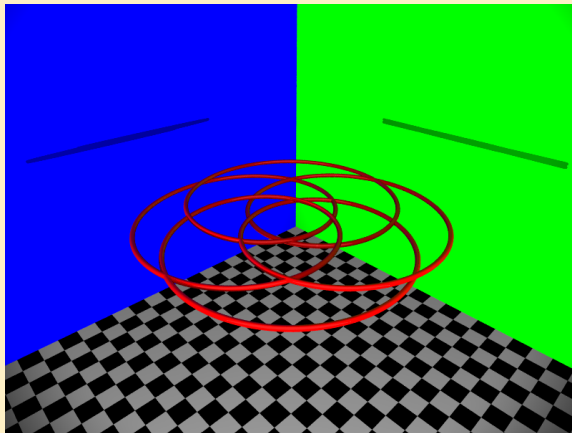
$$x_0(s) = \left(-\frac{5}{2} \cos(s) + 4 \cos(5s), -\frac{5}{2} \sin(s) + 4 \sin(5s), \delta \sin(3s)\right), \quad \delta = 0.0$$

 $t = 0.0$  $t = 685.7$  $t = 2987.4$  $t = 4850.1$  $t = 7965.8$  $t = 10630.6$ 

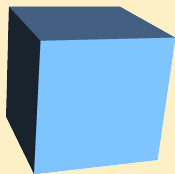
[  $n = 3$ ,  $N = 200$ ,  $\tau = \Delta x = 0.5493$ ,  $\lambda = 0.025$  ]

cf. [Dziuk et al. '06]

# ■ Evolution of a vertically perturbed hypocycloid

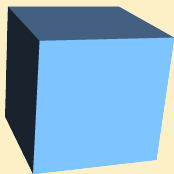


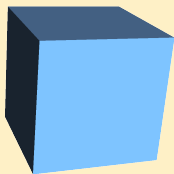
cf. [Dziuk et al. '06]

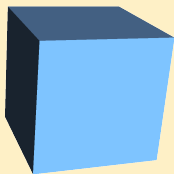


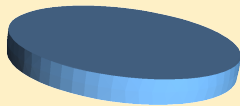
$t = 0$



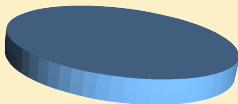
 $t = 0$  $t = \tau \ (\tau = h)$

 $t = 0$  $t = \tau \ (\tau = h)$  $t = 2\tau$

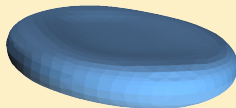
 $t = 0$  $t = \tau \ (\tau = h)$  $t = 2\tau$  $t = 8\tau$



$t = 0$

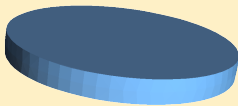


$$t = 0$$

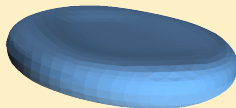


$$t = \tau \quad (\tau = h)$$

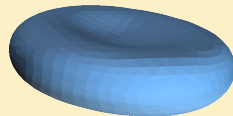
## Willmore flow of surfaces (cont.)



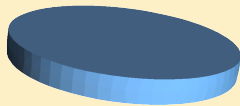
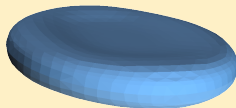
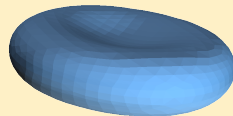
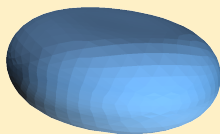
$$t = 0$$

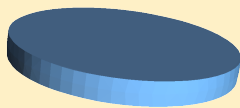


$$t = \tau \quad (\tau = h)$$

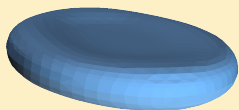


$$t = 6\tau$$

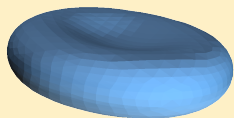
 $t = 0$  $t = \tau \ (\tau = h)$  $t = 6\tau$  $t = 30\tau$



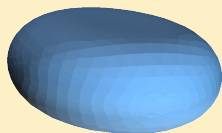
$$t = 0$$



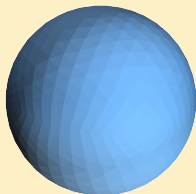
$$t = \tau \quad (\tau = h)$$



$$t = 6\tau$$



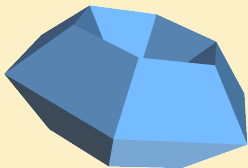
$$t = 30\tau$$



$$t = 430\tau$$

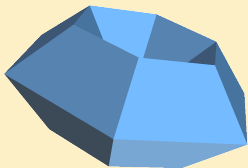


# ■ Willmore flow of surfaces (cont.)

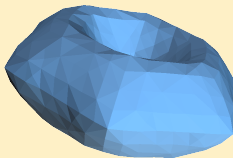


$t = 0$

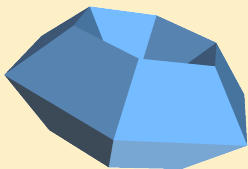
# Willmore flow of surfaces (cont.)



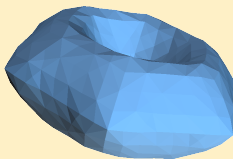
$t = 0$



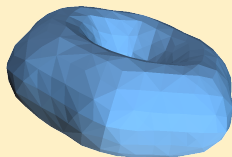
$t = \tau \ (\tau = h^2)$



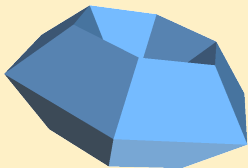
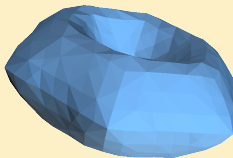
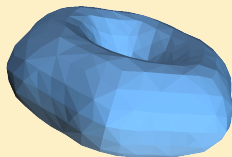
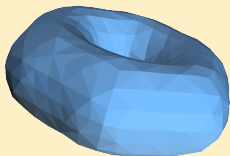
$$t = 0$$

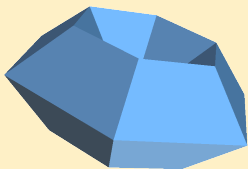
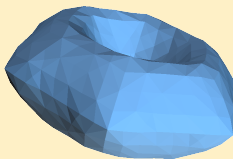
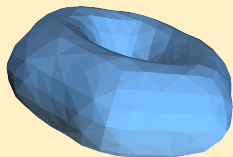
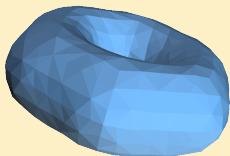
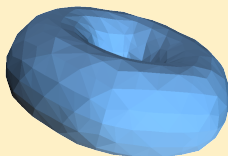


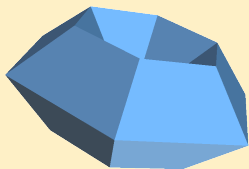
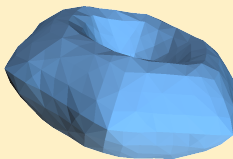
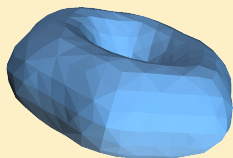
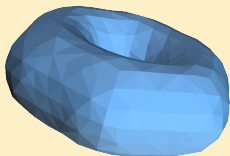
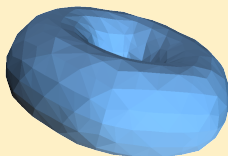
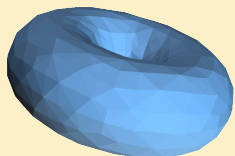
$$t = \tau \quad (\tau = h^2)$$

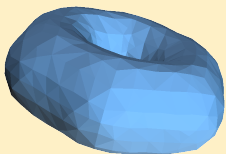


$$t = 2\tau$$

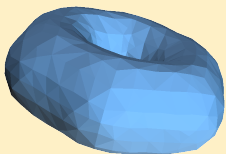
 $t = 0$  $t = \tau \ (\tau = h^2)$  $t = 2\tau$  $t = 3\tau$

 $t = 0$  $t = \tau$  ( $\tau = h^2$ ) $t = 2\tau$  $t = 3\tau$  $t = 10\tau$

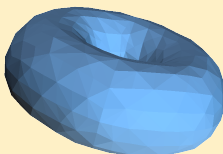
 $t = 0$  $t = \tau$  ( $\tau = h^2$ ) $t = 2\tau$  $t = 3\tau$  $t = 10\tau$  $t = 54\tau$



$$t = 2197 \tau \approx 0.04$$
$$\tau = h^4$$

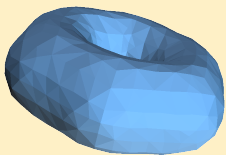


$$t = 2197\tau \approx 0.04$$
$$\tau = h^4$$

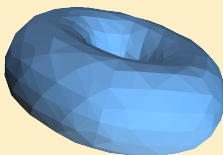


$$t = 13\tau \approx 0.04$$
$$\tau = h^2$$

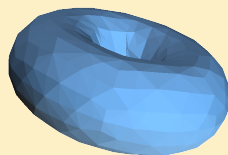




$$t = 2197\tau \approx 0.04$$
$$\tau = h^4$$



$$t = 13\tau \approx 0.04$$
$$\tau = h^2$$



$$t = \tau = 0.04$$
$$\tau = h$$

■

■ *The natural time discretization of gradient flows leads to PDE*

■ *constrained optimization problem.*

■

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*The natural time discretization of gradient flows leads to PDE constrained optimization problem.*

- ✓ The building blocks of the discretization have a direct physical or geometric meaning.

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→ SQP method under development

## Conclusions and Outlook

*The natural time discretization of gradient flows leads to PDE constrained optimization problem.*

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- coupling surface evolution and evolution on the surface

## Conclusions and Outlook

*The natural time discretization of gradient flows leads to PDE constrained optimization problem.*

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- coupling surface evolution and evolution on the surface
- anisotropic Willmore flow

## ■ Details: algorithm for thin film flow

■ In each time step a nonlinear variational problem has to be solved.

■

■

■

■



## ■ Details: algorithm for thin film flow

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■ How to compute the descent direction?

■ **Details: algorithm for thin film flow**

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$$\frac{\partial}{\partial U} E(H(U, H^k))(W) = \partial_H E(\partial_U H(W))$$

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$$H(U, H^k) = L^{-1}(U)H^k$$

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$$\Rightarrow \partial_U H = -L^{-1}(\partial_U L(W))L^{-1}H^k \quad \text{expensive to compute!}$$

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$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

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How to compute the descent direction?

$$\frac{\partial}{\partial U} E(H(U, H^k))(W) = \partial_H E(\partial_U H(W))$$

$$H(U, H^k) = L^{-1}(U)H^k$$

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dual problem:  $L(U)^T P = -\partial_H E$

$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

$$\Rightarrow \frac{\partial}{\partial U} E(W)$$



## Details: algorithm for thin film flow

In each time step a nonlinear variational problem has to be solved.

How to compute the descent direction?

$$\frac{\partial}{\partial U} E(H(U, H^k))(W) = \partial_H E(\partial_U H(W))$$

$$H(U, H^k) = L^{-1}(U)H^k$$

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$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

$$\Rightarrow \frac{\partial}{\partial U} E(W) = \partial_H E(\partial_U H)(W)$$

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dual problem:  $L(U)^T P = -\partial_H E$

$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

$$\Rightarrow \frac{\partial}{\partial U} E(W) = \partial_H E(\partial_U H)(W) = -L^T P \cdot (\partial_U H)(W)$$

In each time step a nonlinear variational problem has to be solved.

How to compute the descent direction?

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$$H(U, H^k) = L^{-1}(U)H^k$$

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dual problem:  $L(U)^T P = -\partial_H E$

$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

$$\begin{aligned} \Rightarrow \frac{\partial}{\partial U} E(W) &= \partial_H E(\partial_U H)(W) = -L^T P \cdot (\partial_U H)(W) \\ &= -P \cdot L(\partial_U H)(W) \end{aligned}$$

In each time step a nonlinear variational problem has to be solved.

How to compute the descent direction?

$$\frac{\partial}{\partial U} E(H(U, H^k))(W) = \partial_H E(\partial_U H(W))$$

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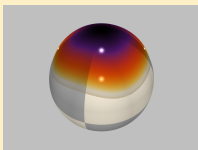
dual problem:  $L(U)^T P = -\partial_H E$

$$H^k = L(U)H(U, H^k) \Rightarrow 0 = (\partial_U L)(W)H + L(\partial_U H)(W)$$

$$\Rightarrow \frac{\partial}{\partial U} E(W) = \partial_H E(\partial_U H)(W) = -L^T P \cdot (\partial_U H)(W)$$

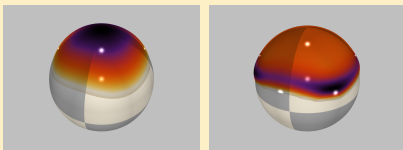
$$= -P \cdot L(\partial_U H)(W) = P \cdot (\partial_U L)(W)H$$

■  
■ Four-fold symmetry perturbed droplet sliding down a sphere:



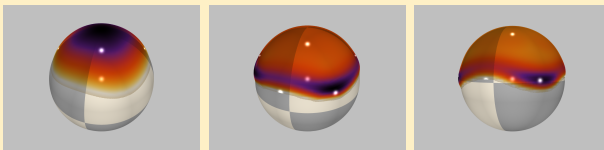
■  
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Four-fold symmetry perturbed droplet sliding down a sphere:

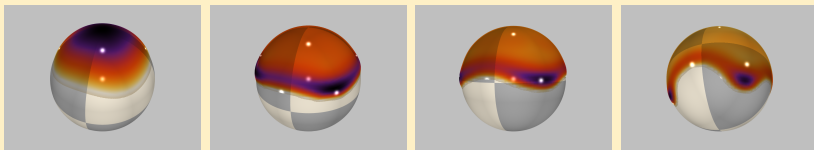


# Droplet on a sphere

Four-fold symmetry perturbed droplet sliding down a sphere:

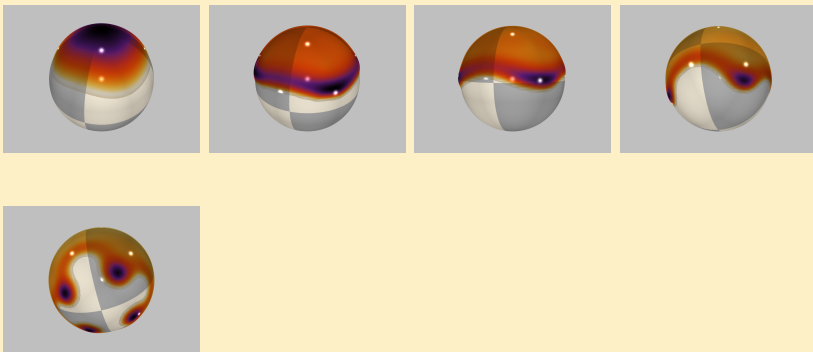


Four-fold symmetry perturbed droplet sliding down a sphere:

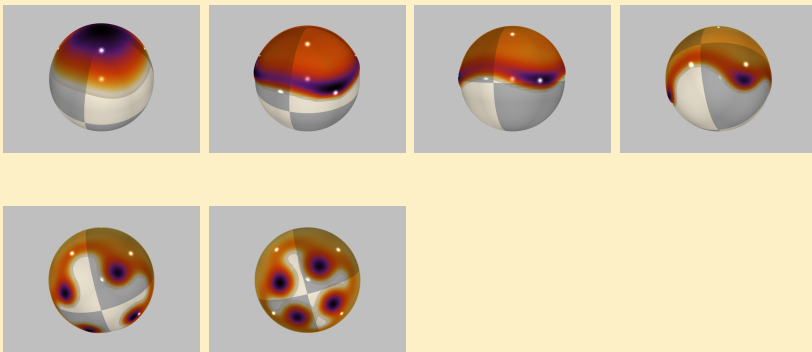




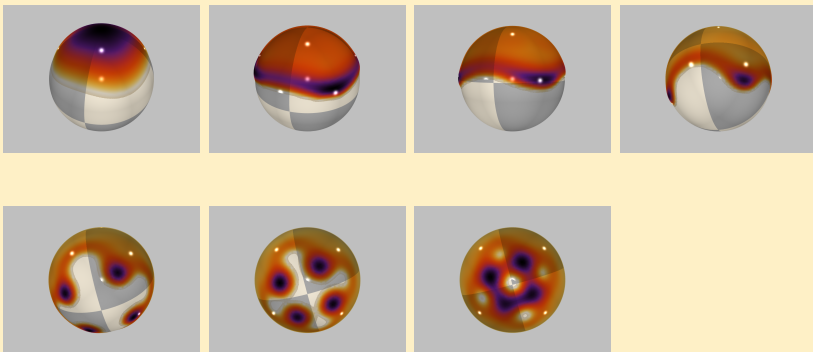
Four-fold symmetry perturbed droplet sliding down a sphere:



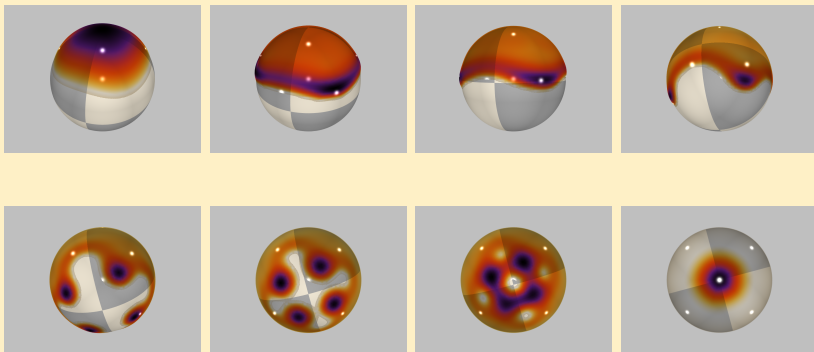
Four-fold symmetry perturbed droplet sliding down a sphere:



Four-fold symmetry perturbed droplet sliding down a sphere:



Four-fold symmetry perturbed droplet sliding down a sphere:



■ In each time step a nonlinear variational problem has to be solved.

■

■

■

■

## Details: algorithm for Willmore flow

In each time step a nonlinear variational problem has to be solved.

How to compute the descent direction?

$$W(X, Y) = \frac{1}{\tau} \int_{\mathcal{S}[X]} |Y - X|^2 da \quad \Rightarrow$$

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$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta) (Y - X) \cdot (Y - X) \\ &\quad + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta - (\partial_X \mathbf{M}(\Theta)) X \cdot P \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P \end{aligned}$$

## Details: algorithm for Willmore flow (cont.)

$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P \\ (\mathbf{M}[X] + \tau \mathbf{L}[X])P &= -\partial_Y W \quad (\text{dual problem}) \end{aligned}$$

Pf.:

$$(\mathbf{M} + \tau \mathbf{L})Y = \mathbf{M}X$$

## Details: algorithm for Willmore flow (cont.)

$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P \\ (\mathbf{M}[X] + \tau \mathbf{L}[X])P &= -\partial_Y W \quad (\text{dual problem}) \end{aligned}$$

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$$(\partial_X \mathbf{M}(\Theta))X = ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y + (\mathbf{M} + \tau \mathbf{L})(\partial_X Y(\Theta)) \Rightarrow$$

## Details: algorithm for Willmore flow (cont.)

$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P \\ (\mathbf{M}[X] + \tau \mathbf{L}[X])P &= -\partial_Y W \quad (\text{dual problem}) \end{aligned}$$

Pf.:

$$\begin{aligned} (\mathbf{M} + \tau \mathbf{L})Y &= \mathbf{M}X \Rightarrow \\ (\partial_X \mathbf{M}(\Theta))X &= ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y + (\mathbf{M} + \tau \mathbf{L})(\partial_X Y(\Theta)) \Rightarrow \\ \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \partial_X W(\Theta) + \partial_Y W(\partial_X Y(\Theta)) \end{aligned}$$

## Details: algorithm for Willmore flow (cont.)

$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P \\ (\mathbf{M}[X] + \tau \mathbf{L}[X]) P &= -\partial_Y W \quad (\text{dual problem}) \end{aligned}$$

Pf.:

$$\begin{aligned} (\mathbf{M} + \tau \mathbf{L}) Y &= \mathbf{M} X \Rightarrow \\ (\partial_X \mathbf{M}(\Theta)) X &= ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y + (\mathbf{M} + \tau \mathbf{L})(\partial_X Y(\Theta)) \Rightarrow \\ \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \partial_X W(\Theta) + \partial_Y W(\partial_X Y(\Theta)) \\ &= \partial_X W(\Theta) - (\mathbf{M} + \tau \mathbf{L}) P \cdot \partial_X Y(\Theta) \end{aligned}$$

## Details: algorithm for Willmore flow (cont.)

$$\frac{\partial}{\partial X} W(X, Y(X))(\Theta) = \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta)) Y \cdot P$$

$$(\mathbf{M}[X] + \tau \mathbf{L}[X])P = -\partial_Y W \quad (\text{dual problem})$$

Pf.:

$$(\mathbf{M} + \tau \mathbf{L})Y = \mathbf{M}X \Rightarrow$$

$$(\partial_X \mathbf{M}(\Theta))X = ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y + (\mathbf{M} + \tau \mathbf{L})(\partial_X Y(\Theta)) \Rightarrow$$

$$\frac{\partial}{\partial X} W(X, Y(X))(\Theta) = \partial_X W(\Theta) + \partial_Y W(\partial_X Y(\Theta))$$

$$= \partial_X W(\Theta) - (\mathbf{M} + \tau \mathbf{L})P \cdot \partial_X Y(\Theta)$$

$$= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta$$

$$- (\mathbf{M} + \tau \mathbf{L})\partial_X Y(\Theta) \cdot P$$

## Details: algorithm for Willmore flow (cont.)

$$\begin{aligned} \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y \cdot P \\ (\mathbf{M}[X] + \tau \mathbf{L}[X])P &= -\partial_Y W \quad (\text{dual problem}) \end{aligned}$$

Pf.:

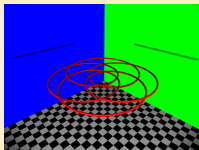
$$\begin{aligned} (\mathbf{M} + \tau \mathbf{L})Y &= \mathbf{M}X \Rightarrow \\ (\partial_X \mathbf{M}(\Theta))X &= ((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y + (\mathbf{M} + \tau \mathbf{L})(\partial_X Y(\Theta)) \Rightarrow \\ \frac{\partial}{\partial X} W(X, Y(X))(\Theta) &= \partial_X W(\Theta) + \partial_Y W(\partial_X Y(\Theta)) \\ &= \partial_X W(\Theta) - (\mathbf{M} + \tau \mathbf{L})P \cdot \partial_X Y(\Theta) \\ &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad - (\mathbf{M} + \tau \mathbf{L})\partial_X Y(\Theta) \cdot P \\ &= \frac{1}{\tau} \partial_X \mathbf{M}(\Theta)(Y - X) \cdot (Y - X) + \frac{2}{\tau} \mathbf{M}(X - Y) \cdot \Theta \\ &\quad + (((\partial_X \mathbf{M} + \tau \partial_X \mathbf{L})(\Theta))Y - (\partial_X \mathbf{M}(\Theta))X) \cdot P \end{aligned}$$



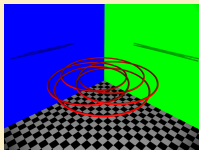
## Evolution of a vertically perturbed hypocycloid

$$x_0(s) = \left(-\frac{5}{2} \cos(s) + 4 \cos(5s), -\frac{5}{2} \sin(s) + 4 \sin(5s), \delta \sin(3s)\right), \quad \delta = 0.1$$

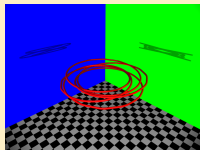
$t = 0.0$



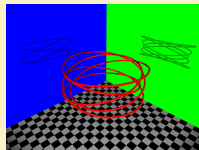
$t = 1348.9$



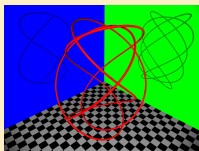
$t = 4264.1$



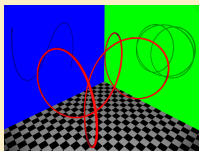
$t = 4670.2$



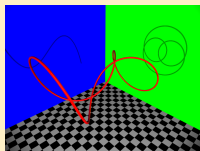
$t = 6555.7$



$t = 9108.4.9$



$t = 9297.0$



$t = 9489.1$

