

# Computational micro-hemodynamics

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# Aim of the Study

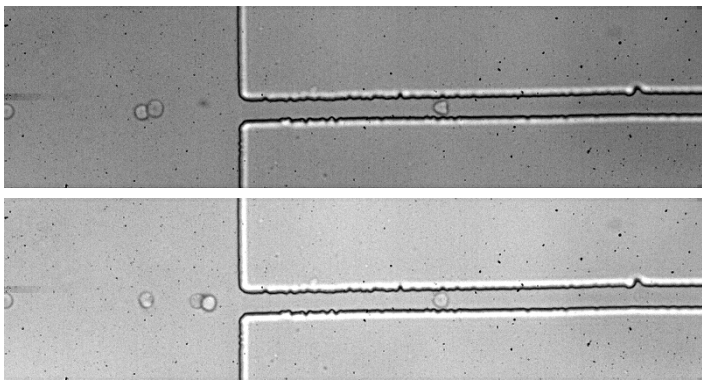
Some points for the motivation:

- ▶ Interest to investigate a complex problem which has a big importance to the health state of an individual
- ▶ Deformability properties of RBCs (and other cells) is currently not clinically used
- ▶ Develop miniaturised diagnosis devices (e.g. lab-on-chip, lab-on-CD), and devices for cell separation
- ▶ Blood test is a common checkup (cheap and not very invasive)

## **Approach:**

Investigate RBC deformability through in-vitro experiments (under a confocal microscope) and **computational simulations** (using Lagrangian particle method - MPS).

## Example of Experimental Results



**Figure** : Single RBC flow in a capillary under different flow rates. (NB. flow is right to left)

## Example of Experimental Results

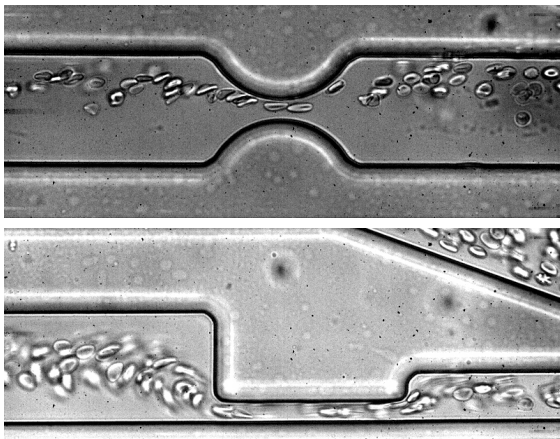
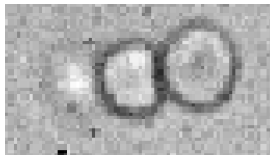
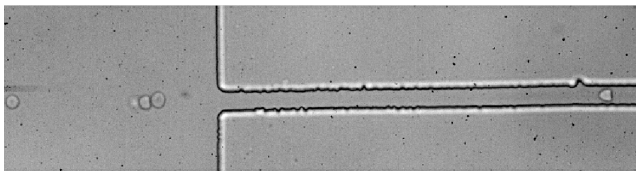


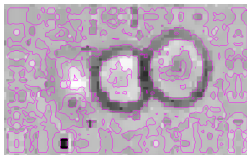
Figure : Flow through constrictions. (NB. flow is right to left)



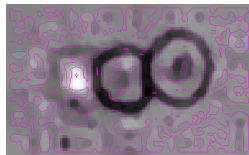
# Image processing



original



Perona-Malik



Novel approach

Figure : Developed automatic image processing methods for filtering, contrast enhancement and segmentation.

# The Moving Particle Semi-implicit method (MPS):

- ▶ mesh-free Lagrangian particle method
- ▶ solves Navier-Stokes equations for an incompressible fluid

$$\frac{1}{\rho} \frac{D\rho}{Dt} + \nabla \cdot \mathbf{u} = 0 \quad ; \quad \frac{D\mathbf{u}}{Dt} = -\frac{\nabla P}{\rho} + \nu \nabla^2 \mathbf{u} + \mathbf{f}$$

it works by:

- ▶ nodal interpolation: compact support radial function
- ▶ derivatives in the Navier-Stokes equations are substituted by discrete operators (strong formulation)
- ▶ is a predictor - corrector method (projection method)

# Compact support and weight function

The particle interactions are restricted to within a finite radius  $r_e$ .

The weighting (shape) function is:

$$w(r) = \begin{cases} \frac{r_e}{r} - 1 & 0 < r < r_e \\ 0 & r_e < r \end{cases}$$

A scalar variable  $\phi$  at any point  $i$  is given by:

$$\phi_i = \frac{1}{\sum_{j=1}^N w(r_{ij})} \sum_{j=1}^N w(r_{ij}) \phi_j$$

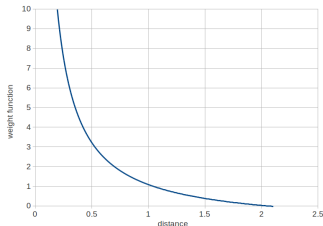
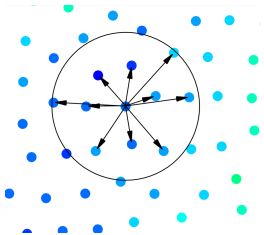


Figure : Example of particle compact support and weight function.

# Incompressibility

- ▶ each particle represents a lumped volume of fluid
- ▶ idea is therefore to keep a constant distribution of particles

Introduce the particle number density at position  $i$  as:

$$n_i = \sum_{j \neq i}^N w(r_{ij})$$

where  $N$  = number of particles;  $r_{ij}$  = distance between particles  $i$  and  $j$ .

For incompressible flows this number should be constant =  $n^0$ .

We note that  $\rho_i \propto n_i$ .

## Time stepping

MPS is a predictor-corrector method:  $\mathbf{u}_i^{n+1} = \mathbf{u}_i^* + \mathbf{u}_i^{**}$ , where  $*$  and  $**$  denote the predictor and corrector stages, and  $\mathbf{x}_i^{n+1} = \mathbf{x}_i^n + \Delta t \cdot \mathbf{u}_i^{n+1}$ .

The **momentum** equation  $\left( \frac{D\mathbf{u}}{Dt} = -\frac{\nabla P}{\rho} + \nu \nabla^2 \mathbf{u} + \mathbf{f} \right)$

$$\frac{D\mathbf{u}}{Dt} = \frac{\mathbf{u}^{n+1} - \mathbf{u}^n}{\Delta t} = \frac{\mathbf{u}^{**} + (\mathbf{u}^* - \mathbf{u}^n)}{\Delta t} = -\frac{\nabla p}{\rho} + (\mathbf{f} + \nu \nabla^2 \mathbf{u})$$

predictor :  $\mathbf{u}^* = \mathbf{u}^n + \Delta t(\mathbf{f} + \nu \nabla^2 \mathbf{u})$  ; corrector :  $\mathbf{u}^{**} = -\frac{\Delta t}{\rho} \nabla p$

The **continuity** equation  $\left( \frac{1}{\rho} \frac{D\rho}{Dt} + \nabla \cdot \mathbf{u} = 0 \right)$

$$\frac{1}{\rho} \frac{D\rho}{Dt} = \frac{\rho^{n+1} - \rho^n}{\rho \Delta t} = \frac{\rho^{**} + (\rho^* - \rho^n)}{\rho \Delta t} = -\nabla \cdot (\mathbf{u}^{**} + \mathbf{u}^*)$$

predictor :  $\frac{1}{\rho} \frac{\rho^* - \rho^n}{\Delta t} = -\nabla \cdot \mathbf{u}^*$  ; corrector :  $\frac{1}{\rho} \frac{\rho^{**}}{\Delta t} = -\nabla \cdot \mathbf{u}^{**}$

# Time stepping

(from previous slide)

$$\text{predictor : } \mathbf{u}^* = \mathbf{u}^n + \Delta t(\mathbf{f} + \nu \nabla^2 \mathbf{u}) \quad ; \quad \text{corrector : } \mathbf{u}^{**} = -\frac{\Delta t}{\rho} \nabla p$$

$$\text{predictor : } \frac{1}{\rho} \frac{\rho^* - \rho^n}{\Delta t} = -\nabla \cdot \mathbf{u}^* \quad ; \quad \text{corrector : } \frac{1}{\rho} \frac{\rho^{**}}{\Delta t} = -\nabla \cdot \mathbf{u}^{**}$$

For incompressibility  $\frac{D\rho}{Dt} = 0$ , hence  $n^0 = n^* + n^{**}$ .

$$\text{Since } \rho \propto n; \quad \frac{1}{\rho} \frac{\rho^{**}}{\Delta t} = \frac{1}{n^0} \frac{n^{**}}{\Delta t} = -\nabla \cdot \mathbf{u}^{**}.$$

$$\text{Substitution in } \mathbf{u}^{**} = -\frac{\Delta t}{\rho} \nabla p \text{ we obtain} \quad \nabla^2 p = \frac{-\rho}{\Delta t^2} \frac{n^* - n^0}{n^0}$$

## Summary of method

Step	Equation
predictor stage	$\mathbf{u}^* = \mathbf{u}^n + \Delta t(\mathbf{f}) + \Delta t(\nu \nabla^2 \mathbf{u}^*)$ $\mathbf{x}_i^* = \mathbf{x}_i^n + \Delta t \cdot \mathbf{u}_i^*$
compute pressure	$\nabla^2 p = \frac{-\rho}{\Delta t^2} \frac{(n^* - n^0)}{n^0}$
corrector stage	$\mathbf{u}^{n+1} = \mathbf{u}^* + \mathbf{u}^{**} = \mathbf{u}^* - \frac{\Delta t}{\rho} \nabla p^{n+1}$ $\mathbf{x}_i^{n+1} = \mathbf{x}_i^n + \Delta t \cdot \mathbf{u}_i^{n+1}$

# Differential operators

The **gradient** in MPS is given by:

$$\nabla\phi_i = \frac{d}{n^0} \sum_{j \neq i}^N w(r_{ij}) \frac{(\phi_j - \phi_i)(\mathbf{x}_j - \mathbf{x}_i)}{|\mathbf{x}_j - \mathbf{x}_i|^2}$$

while the **Laplacian** is modelled as:

$$\nabla^2\phi_i = \frac{2d}{\lambda n^0} \sum_{j \neq i}^N w(r_{ij})(\phi_j - \phi_i)$$

where:  $\lambda = \frac{\sum_{j \neq i}^N w(r_{ij})r_{ij}^2}{\sum_{j \neq i}^N w(r_{ij})}$ ;  
 $d = 3$  in 3D and  $d = 2$  in 2D.



## Summary of method

Step	Equation
predictor stage	$\mathbf{u}_i^* = \mathbf{u}_i^n + \Delta t \left( \nu \frac{2d}{\lambda n^0} \left( \sum_{j \neq i}^N w(r_{ij}) (\mathbf{u}_j^* - \mathbf{u}_i^*) \right) + \mathbf{f} \right)$ $\mathbf{r}_i^* = \mathbf{r}_i^n + \Delta t \cdot \mathbf{u}_i^*$
particle number	$n_i^* = \sum_{j \neq i}^N w(r_{ij})$
pressure	$\sum_{j \neq i}^N \left( w(r_{ij}) P_j^{n+1} \right) - P_i^{n+1} \left( \sum_{j \neq i}^N w(r_{ij}) \right) = - \frac{\rho \lambda (n_i^* - n^0)}{\Delta t^2 2d}$
pressure gradient	$\nabla P_i^{n+1} = \frac{d}{n_i^*} \sum_{j \neq i}^N w(r_{ij}) (P_j^{n+1} - (P_i^{n+1})) \frac{(\mathbf{r}_j - \mathbf{r}_i)}{ \mathbf{r}_{ij} ^2}$
corrector stage	$\mathbf{u}_i^{n+1} = \mathbf{u}_i^* - \Delta t \frac{1}{\rho} \nabla P_i^{n+1}$ $\mathbf{r}_i^{n+1} = \mathbf{r}_i^n + \Delta t \cdot \mathbf{u}_i^{n+1}$

# Modelling RBCs

In simulating blood in small vessels, the constitutive components (i.e. the cells) must be modelled.

The approach is to use a spring network model for the membranes:

- ▶ tension/compression spring
- ▶ bending spring
- ▶ penalisation force (e.g. area and volume constraints)

Springs act as body force terms in the predictor stage.

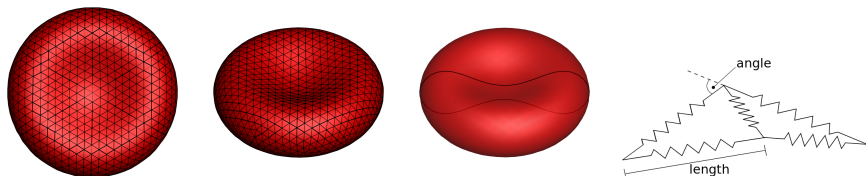


Figure : Red blood cell membrane spring network model.

## Results: Different structural parameters

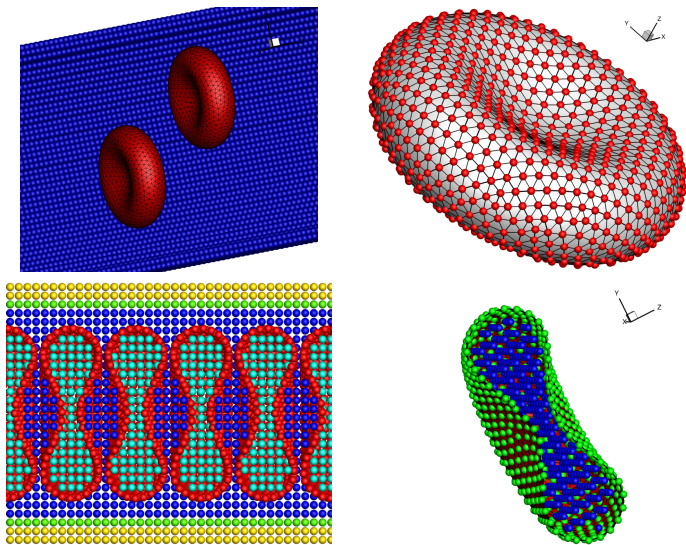
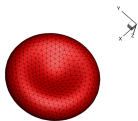
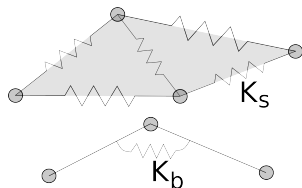
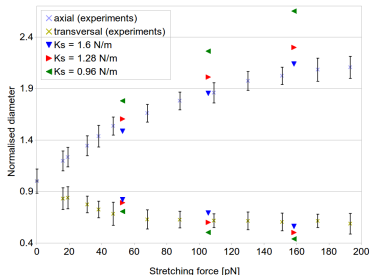
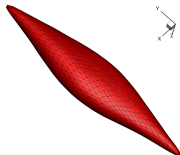


Figure : Discretisation of the domain and red blood cells.

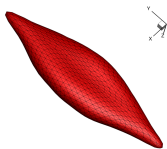
# Testing different spring stiffness coefficients



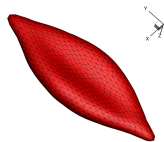
at rest



$9.6 \mu\text{Nm}$



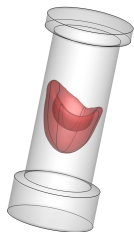
$12.8 \mu\text{Nm}$



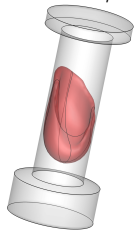
$16.0 \mu\text{Nm}$

Figure : Testing static stretching with 100 pN force,  $K_b = 3.2 \times 10^{-11}$  N.

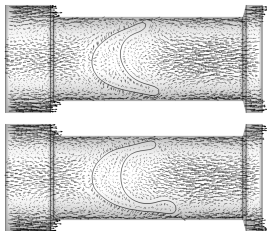
# Results of flow simulations



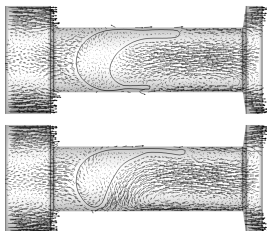
$\Delta p = 12.1$  Pa,  
diameter= $7.8\mu\text{m}$



$\Delta p = 20$  Pa,  
diameter= $6\mu\text{m}$



relative velocity in two orthogonal planes



relative velocity in two orthogonal planes

Figure : RBC flowing in a constricted vessel, showing cross sections of the relative velocity ( $u' = u - \bar{u}$ ).

# Results of flow simulations

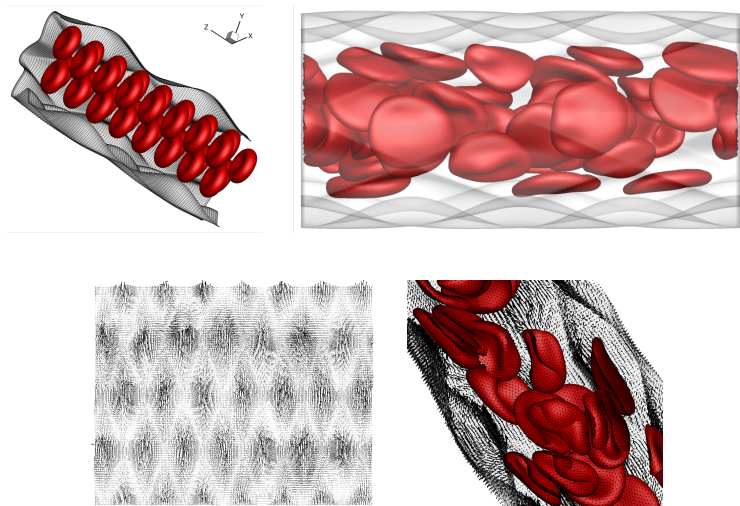


Figure : RBC flowing in small vessel - modelling endothelial cells.

## Results: RBCs in straight pipe

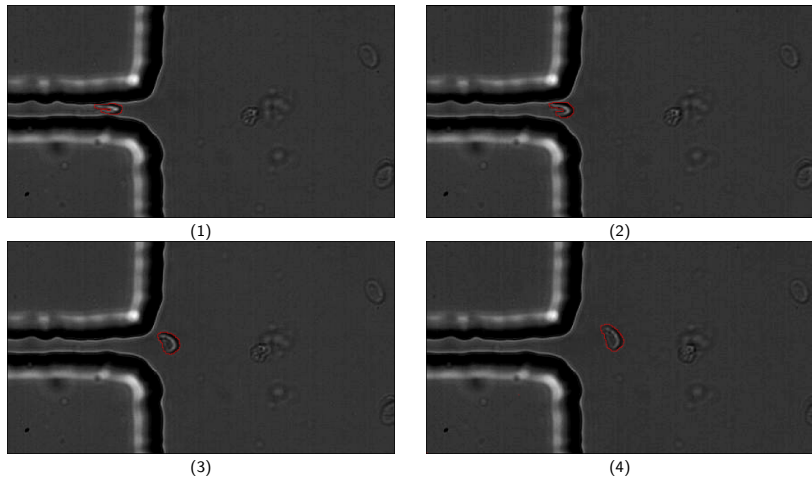
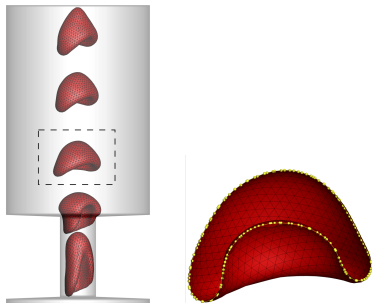
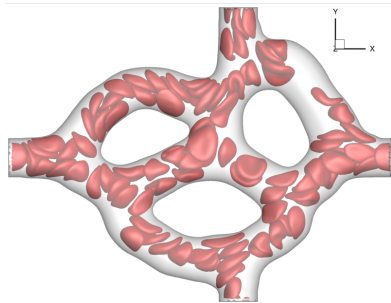


Figure : Experiment of RBC flowing in small constriction.

# Results of flow simulations



Simulations in a  
discontinuous constriction



RBC flowing in model capillary .  
network of the retina



# Conclusions and Future Work

## Conclusion:

- ▶ can perform RBC tracking of experimental data;
- ▶ can simulate blood flow in capillaries;
- ▶ can compare with some benchmark studies.

## Future Work:

- ▶ more benchmark studies;
- ▶ model cell adhesion;
- ▶ model cell hemolysis;
- ▶ observe cell migration in relation to the flow field;
- ▶ use simulation to develop devices for studying patient specific properties;

## **FUNDING:**

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## **COLLABORATORS:**

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- ▶ Ana João, Jorge Tiago (Instituto Superior Técnico, CEMAT)
- ▶ Rui Lima & co-workers (Polytechnic Institute of Bragança, ESTiG/IPB)

## Gradient operator

Given a scalar quantity  $\phi$ , the gradient vector for particles at positions  $\mathbf{x}_i$  and  $\mathbf{x}_j$  is:  $\nabla\phi_{ij} = \frac{(\phi_j - \phi_i)}{|\mathbf{x}_j - \mathbf{x}_i|} \cdot \frac{(\mathbf{x}_j - \mathbf{x}_i)}{|\mathbf{x}_j - \mathbf{x}_i|}$

The gradient in MPS, where there are several neighbouring particles  $j$  and an interpolation is performed using the weight function, is written as:

$$\nabla\phi_i = \frac{d}{n^0} \sum_{j \neq i}^N w(r_{ij}) \frac{(\phi_j - \phi_i)(\mathbf{x}_j - \mathbf{x}_i)}{|\mathbf{x}_j - \mathbf{x}_i|^2}$$

where  $d$  is the number of space dimensions, hence  $d = 3$  in 3D and  $d = 2$  in 2D.

# Laplacian operator

The Laplacian is modelled as diffusion problem:  $\frac{d\phi}{dt} = \alpha \nabla^2 \phi$  with  $\alpha > 0$ .

For an initial condition of a point source of unit magnitude, the solution is given by  $\phi(x, t) = \left(\frac{1}{\sqrt{4\pi\alpha t}}\right)^d \exp\left(-\frac{r^2}{4\alpha t}\right)$ , hence a normal distribution with mean = 0 and variance =  $2d\alpha t$ .

The variance distribution of  $\phi$  increases by  $2d\alpha\Delta t$  during time step  $\Delta t$ . Therefore the quantity transferred from particle  $i$  to the neighbouring particles should have the same variance increase:

$$\Delta\phi_{i \rightarrow j} = \frac{2d\alpha\Delta t}{\lambda n^0} \phi_i w(r_{ij})$$

A normalisation appears due to the discretisation  $\lambda = \frac{\sum_{j \neq i}^N w(r_{ij}) r_{ij}^2}{\sum_{j \neq i}^N w(r_{ij})}$ .

Putting it all together:  $\nabla^2 \phi_i = \frac{2d}{\lambda n^0} \sum_{j \neq i}^N w(r_{ij}) (\phi_j - \phi_i)$