

A Level-Set Framework for Shape Optimisation

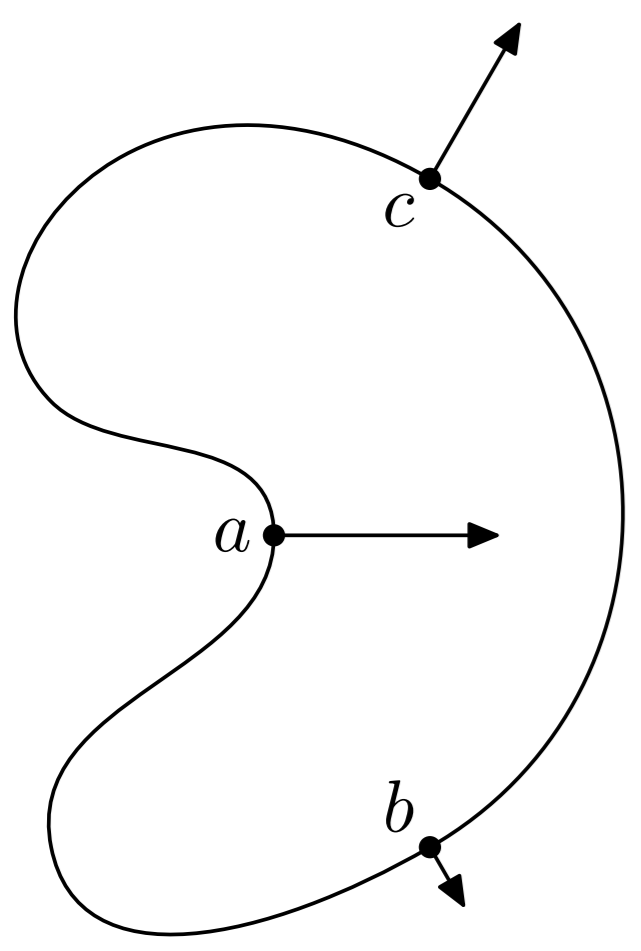
Daniel Kraft (KFU), Michael Ulbrich (TUM), Wolfgang Ring (KFU)

The Level-Set Method

For a level-set function $\phi: \mathbb{R}^n \rightarrow \mathbb{R}$, we define:

$$\Omega = \phi^{-1}((-\infty, 0)) = \{x \in \mathbb{R}^n \mid \phi(x) < 0\},$$

$$\Gamma = \phi^{-1}(\{0\}) = \{x \in \mathbb{R}^n \mid \phi(x) = 0\}$$

Evolution of $\Omega_0 \subset \mathbb{R}^n$ by the speed method:

Propagation in time with the level-set equation:

$$\phi_t + F(x) |\nabla \phi| = 0 \quad (1)$$

 $F \in C^{0,1}(\mathbb{R}^n)$ is a scalar speed field.Left: $F(a) < 0 < F(b) < F(c)$

State of the Art

- Solution theory for (1) well-established (viscosity solutions); see Giga [10].
- Many successful applications in engineering without rigorous foundation.
- Sethian's Fast Marching Method for efficient numerical computation.
- Some analysis of optimisation in a functional-analytic context; see Burger [9].

Our contribution: A solid measure-theoretic and geometric foundation for the level-set based speed method in shape optimisation.

A Hopf-Lax Representation Formula

The level-set equation (1) can be interpreted as the Hamilton-Jacobi-Bellman equation of a control problem.

If we define the F -induced distance

$$d(x, y) = \inf_{\xi: x \rightsquigarrow y} \int_0^1 \frac{|\xi'(\tau)|}{F(\xi(\tau))} d\tau, \quad d_0(x) = \inf_{y \in \Omega_0} d(x, y),$$

this gives the time evolution:

$$\phi(x, t) = \inf \{\phi_0(y) \mid d(x, y) \leq t\}, \quad \Omega_t = \{x \in \mathbb{R}^n \mid d_0(x) < t\} \quad (2)$$

Efficient computation of d_0 is possible with the Fast Marching Method to solve the Eikonal equation

$$F(x) |\nabla d_0| = 1, \quad d_0 = 0 \text{ on } \overline{\Omega_0}.$$

Shape Sensitivity Analysis

One can use (2) to express a domain functional:

$$J(\Omega_t) = \int_{\Omega_t} f dx = J(\Omega_0) + \int_0^t \int_{\Gamma_s} Ff d\sigma ds$$

This yields a shape calculus that requires little regularity of the involved domains and speed fields.

For shape-dependent integrands like $J(\Omega) = \int_{\Omega} f(x, \Omega) dx$, we get

$$dJ(\Omega; F) = \int_{\Gamma} Ff d\sigma + \int_{\Omega} f' dx.$$

Non-Fattening

Classical result by Barles, Soner, Souganidis [8]:

$$\{(x, t) \mid \phi(x, t) \leq 0\} = \overline{\{(x, t) \mid \phi(x, t) < 0\}},$$

$$\{(x, t) \mid \phi(x, t) < 0\} = \{(x, t) \mid \phi(x, t) \leq 0\}^\circ$$

With (2), we can show naturally:

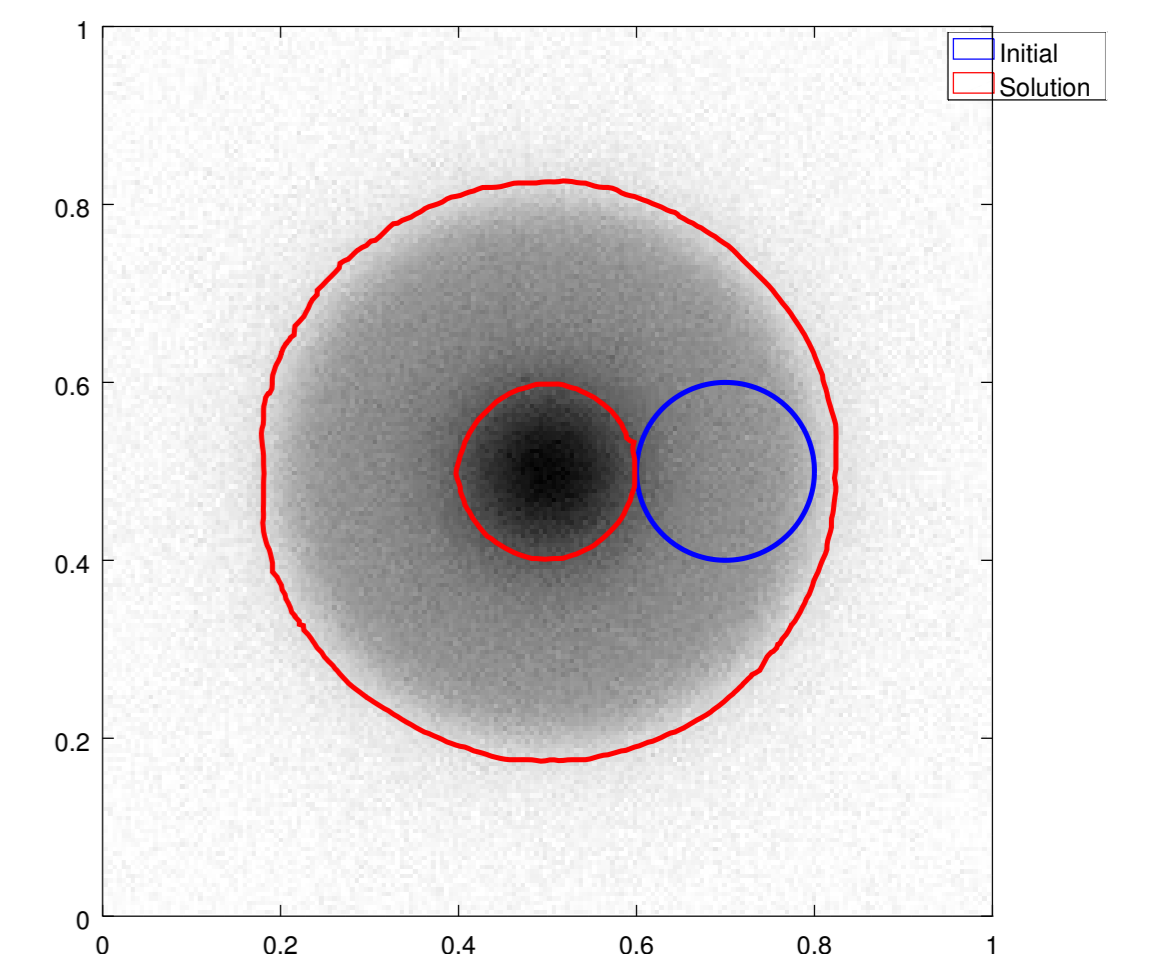
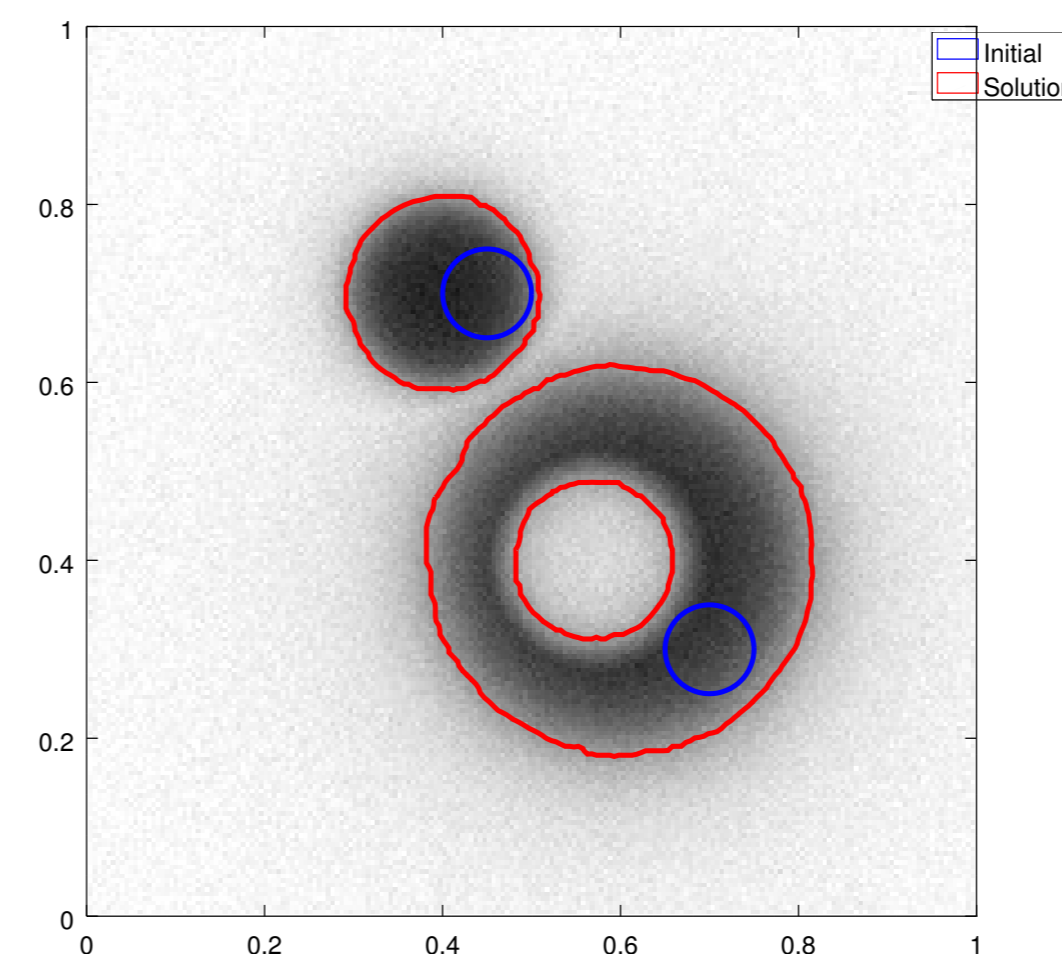
$$F \geq 0 \Rightarrow \overline{\Omega}_t = \Gamma_t \cup \Omega_t,$$

$$F < 0 \Rightarrow (\Gamma_t \cup \Omega_t)^\circ = \Omega_t$$

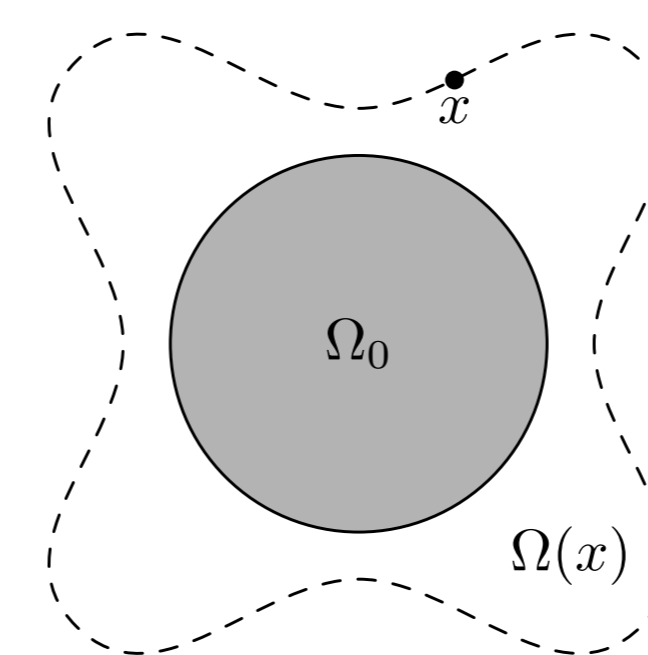
Image Segmentation

Consider this example problem for image segmentation:

$$J(\Omega) = \int_{\Omega} (u(x) - \bar{u})^2 dx - 2\gamma \cdot \sigma \cdot \text{vol}(\Omega)$$



Self-Consistent Gradient Flow



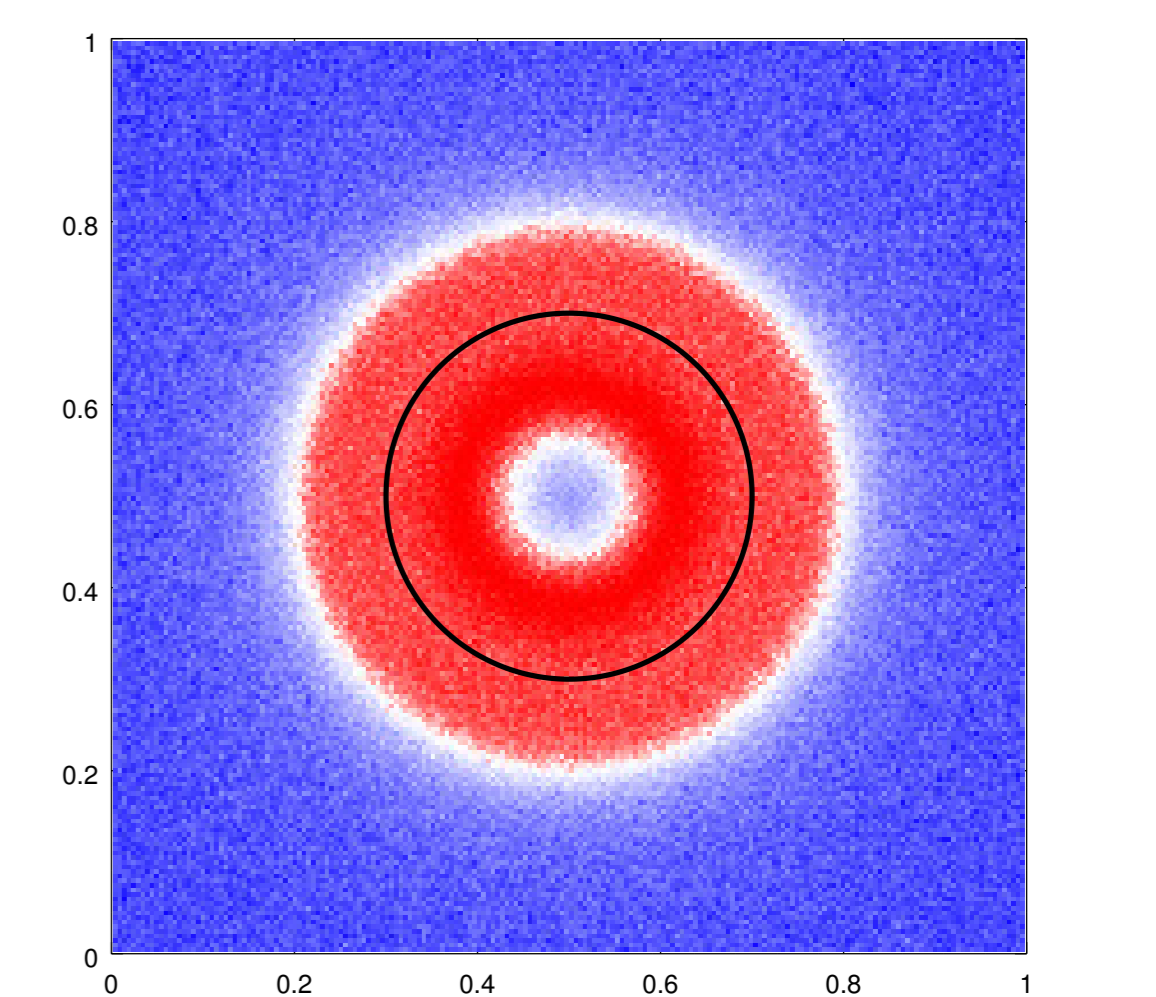
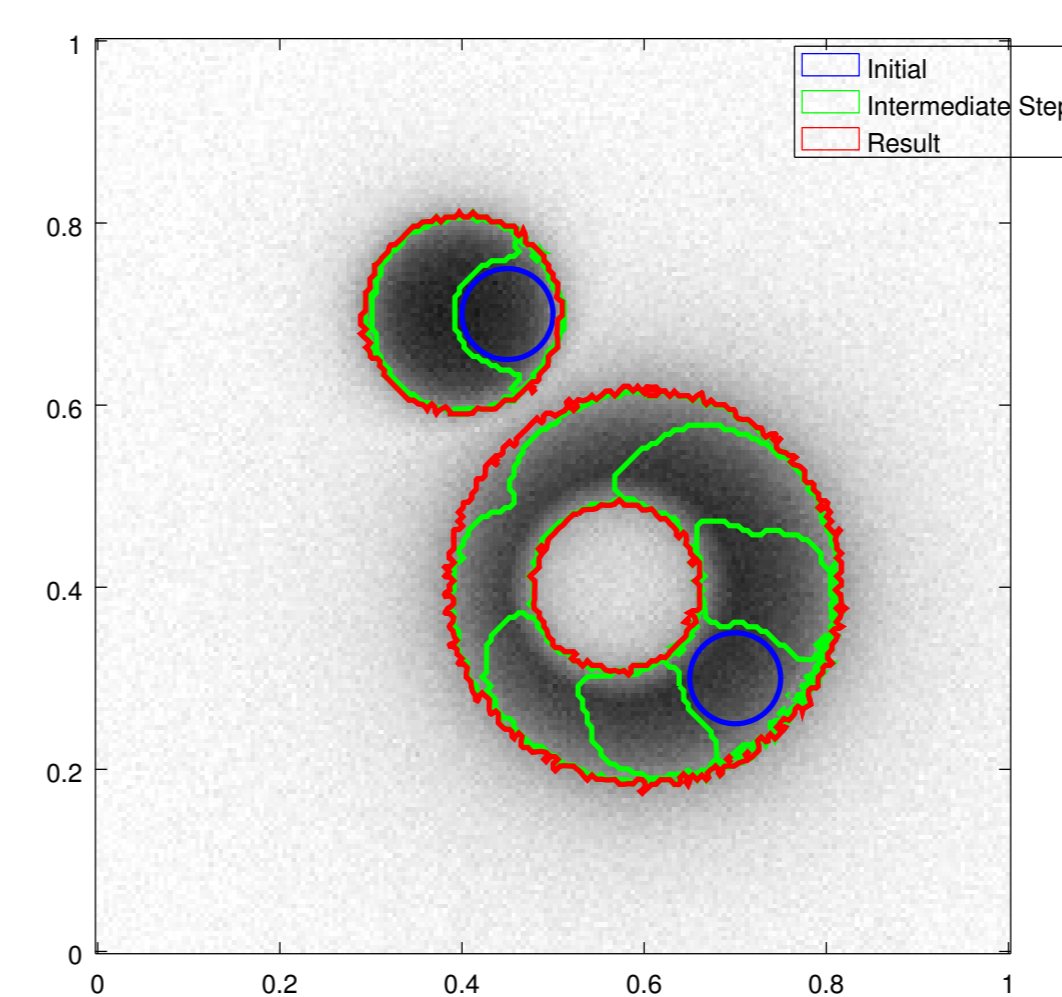
Assume the shape derivative

$$dJ(\Omega; F) = \int_{\Gamma} Ff(x, \Omega) d\sigma.$$

We want a self-consistent steepest descent:

$$\psi(F)(x) = F(x) = -f(x, \Omega(x))$$

Under suitable assumptions, existence of a fixed-point speed field can be shown. This gives a self-consistent gradient flow.



PDE-Constrained Shape Optimisation

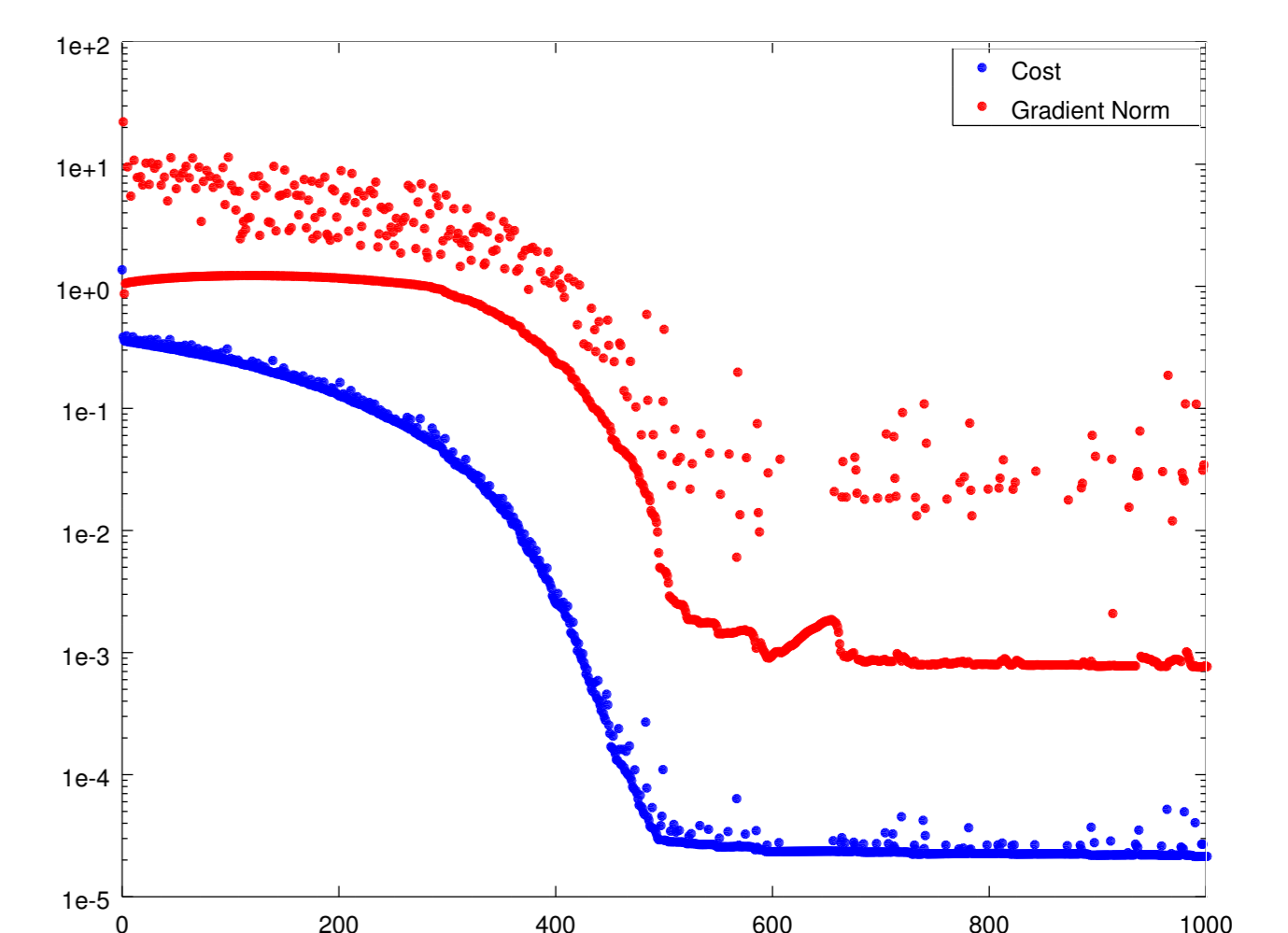
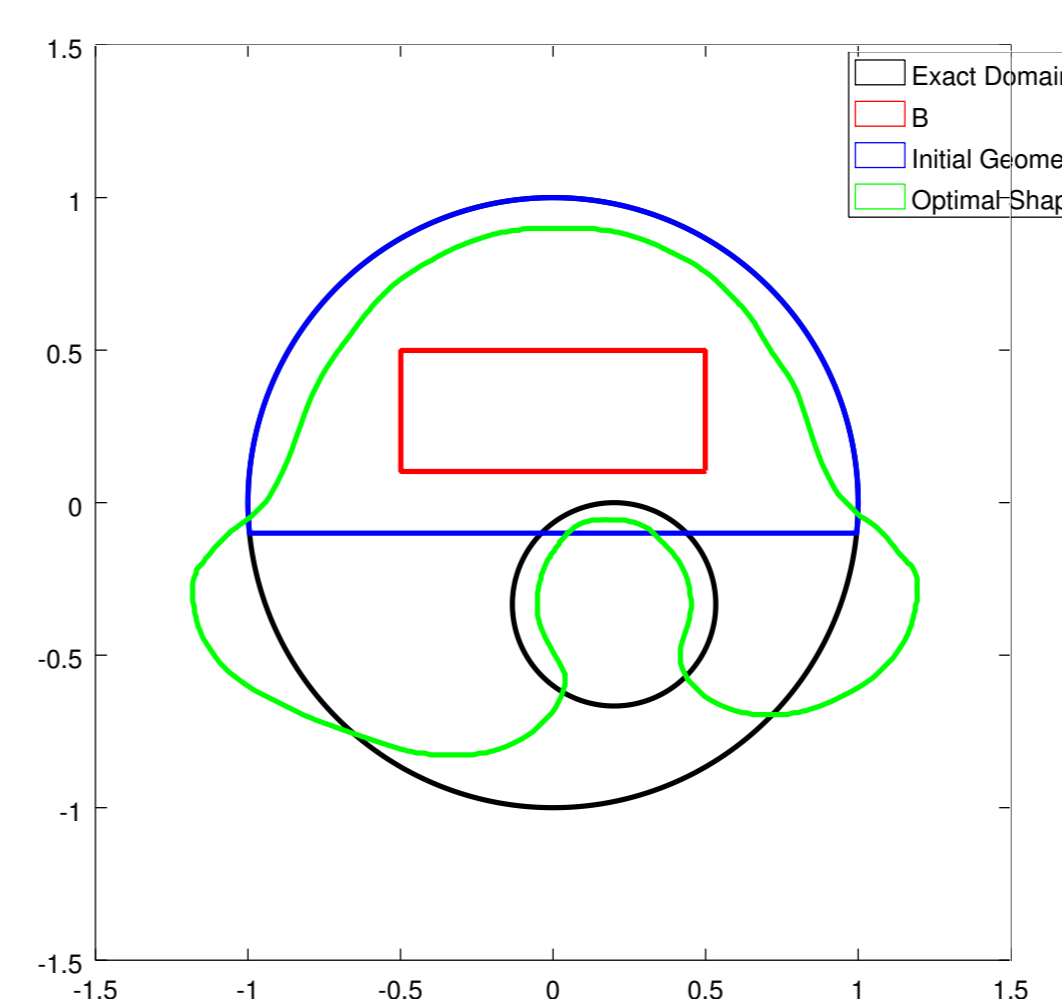
For $f \in L^2(D)$ and $u_d \in L^2(B)$, minimise (with $B \subset \Omega \subset D$):

$$J(\Omega) = \int_B (u - u_d)^2 dx + R(\Omega),$$

$$-\Delta u + u = f \text{ in } \Omega, \quad \frac{\partial u}{\partial \nu} = 0 \text{ on } \partial\Omega$$

Shape derivative with adjoint approach:

$$dJ(\Omega; F) = \int_{\Gamma} (fp - \langle \nabla u, \nabla p \rangle - up)F d\sigma + dR(\Omega; F)$$



Individual Publications

- [1] M. Keuthen and D. Kraft. Shape Optimization of a Breakwater. *Inverse Problems in Science and Engineering* (accepted), 2015.
- [2] D. Kraft. Difficulty Control for Blockchain-Based Consensus Systems. *Peer-to-Peer Networking and Applications*, 2015.
- [3] D. Kraft. Measure-Theoretic Properties of Level Sets of Distance Functions. *Journal of Geometric Analysis*