EPDiff and Optimal Control of Shapes

Colin Cotter, Department of Aeronautics, Imperial College London

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- Numerical examples

EP equation and optimal control

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$$Q(0) = Q_0, \quad Q(1) = Q_1$$

see Bloch, Crouch, Marsden & Ratiu, 1998

$$\delta \int_0^1 \frac{1}{2} \Omega \cdot I\Omega + P^T \cdot (\dot{Q} - Q\Omega) \, \mathrm{d}t = 0$$

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$$I\Omega = Q^T P,$$

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$$\begin{array}{rcl} \frac{d}{dt}I\Omega & = & \dot{Q}^TP + Q^T\dot{P}, \\ & = & (Q\Omega)^TP + Q^TP\Omega, \\ & = & \Omega^T(Q^TP) + (Q^TP)\Omega, \\ & = & \Omega^T(I\Omega) + (I\Omega)\Omega. \end{array}$$

When in general can P and Q be eliminated from the dynamical equations?

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Hamiltonian $H = \ell(\xi(P, Q))$

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and $P \diamond Q$ is a cotangent-lifted momentum map

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- * See: Marsden and Bou-Rabee (2007) and Cotter and Holm (submitted 2007)

Variational image matching

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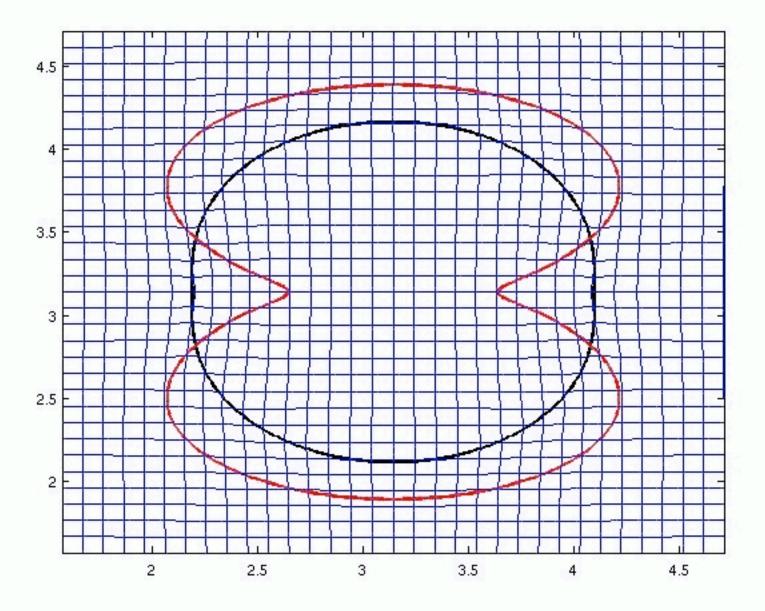
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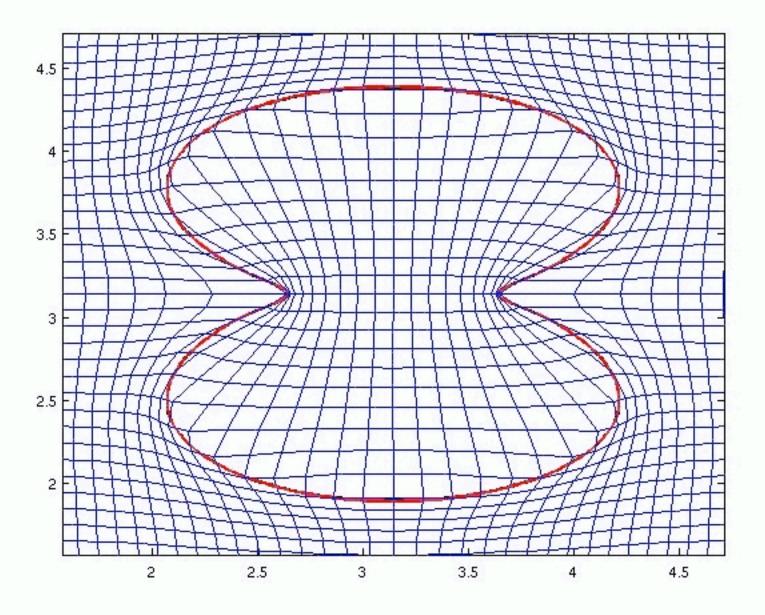
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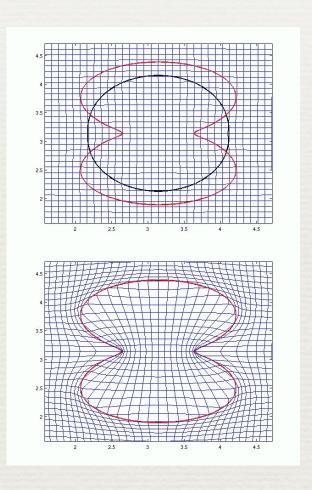
All of these spaces have roles in imaging For the rest of the talk specialise to embeddings What does the shortest path between two shapes look like?





What can we do with these paths?

- Length along path measures amount of deformation from one shape to another
- * A way of comparing and classifying shapes
- Deformation from one shape to another is encoded in initial conditions for deformation velocity field, where we can perform linear statistics



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and

$$\mathbf{Q}_0(s) = \mathbf{Q}^A(s), \quad \forall s \in (0, 2\pi], \qquad \mathbf{Q}_1 \equiv \mathbf{Q}^B$$

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- * For now, matching condition is a "soft constraint" enforced *via* penalty term

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Euler-Lagrange equations for *t*<1

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where

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Equations become

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For any choice of norm, we can eliminate P and Q to get an equation purely in terms of u

$$\frac{\partial}{\partial t} \boldsymbol{m} + \operatorname{ad}_{\boldsymbol{u}}^* \boldsymbol{m} = \frac{\partial}{\partial t} \boldsymbol{m} + \nabla \cdot (\boldsymbol{u} \boldsymbol{m}) + (\nabla \boldsymbol{u})^T \boldsymbol{m} = 0$$

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In 1-dimension this becomes (Camassa and Holm, 1993)

$$m_t + \frac{\partial m}{\partial x}u + 2\frac{\partial u}{\partial x}m = 0, \qquad m = u - \alpha^2 \frac{\partial^2 u}{\partial x^2}$$

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$$d\mu_{A}(\boldsymbol{x}) = \int_{S} \hat{\mu}_{A}(s)\delta(\boldsymbol{x} - \boldsymbol{Q}^{A}(s)) ds dV(\boldsymbol{x})$$

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Penalty functional is

$$f[\mathbf{Q}_1] = \int_{\Omega} \int_{\Omega} K(\mathbf{x}, \mathbf{y}) d\nu(\mathbf{x}) d\nu(\mathbf{y}), \quad d\nu = d\mu_B - d\mu_1$$

Momentum

- * Geodesic is determined by initial conditions for shape coordinates *Q* and conjugate momenta *P*
- * Given a reference shape, have an isomorphism between any topologically equivalent shape and initial conditions for *P*
- * *P* is in a linear space so we can apply linear statistical techniques to this representation

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- * The optimal solution has momentum which is normal to the shape (see Miller, Trouvé and Younes (2003))

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This is closely linked to the Clebsch representation of fluid dynamics, and the Kelvin circulation theorem

Particle-mesh discretisation

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- * Velocity represented on a fixed mesh
- * Closely related to Hamiltonian particle-mesh method (HPM) for shallow-water equations (Frank, Gottwald, Reich)

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Now restrict to a finite set of points $\{Q_{\beta}\}_{\beta=1}^{n_p}$

$$\dot{oldsymbol{Q}}_eta = \sum_k oldsymbol{u}_k \psi_k(oldsymbol{Q}_eta)$$

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$$\min_{\boldsymbol{u},\boldsymbol{Q},\boldsymbol{P}} \left(\int_0^1 \left(\|\boldsymbol{u}_t\|^2 + \int_S \boldsymbol{P}_t(s) \cdot \left(\frac{\partial}{\partial t} \boldsymbol{Q}_t(s) - \int_{\boldsymbol{\Omega}} \boldsymbol{u}_t(\boldsymbol{x}) \delta(\boldsymbol{x} - \boldsymbol{Q}_t(s)) dV(\boldsymbol{x}) \right) ds \right) dt + \frac{1}{\sigma^2} f[\boldsymbol{Q}_1] \right)$$

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We adopt a **geometric approach** by trying to exactly optimise a discretised functional

$$\min_{\boldsymbol{u},\boldsymbol{Q},\boldsymbol{P}} \left(\int_0^1 \left(\|\boldsymbol{u}\|_g^2 + \sum_{\beta} \boldsymbol{P}_{\beta} \cdot \left(\dot{\boldsymbol{Q}}_{\beta} - \sum_k \boldsymbol{u}_k \psi_k(\boldsymbol{Q}_{\beta}) \right) \right) dt + \frac{1}{\sigma^2} \hat{f}(\boldsymbol{Q}(1)) \right)$$

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\frac{\partial}{\partial t} \boldsymbol{Q}_{t}(s) & = & \boldsymbol{u}_{t}(\boldsymbol{Q}_{t}(s)) \\
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\end{vmatrix}$$

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$$\mu_k^1 = \sum_{\beta} \hat{\mu}_{\beta}^A \psi_k(\boldsymbol{Q}_{\beta}(1))$$

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$$\hat{f}(\mathbf{Q}(1)) = \sum_{kl} K_{kl} \nu_k \nu_l, \quad \nu_k = \mu_k^1 - \mu_k^B$$

Time discretisation

Discretise in time in the functional

$$\min_{\boldsymbol{u},\boldsymbol{Q},\boldsymbol{P}} \left(\Delta t \sum_{n=1}^{N} \left(\|\boldsymbol{u}^{n-1}\|_{g}^{2} + \sum_{\beta} \boldsymbol{P}_{\beta}^{n-1} \cdot \left(\frac{\boldsymbol{Q}_{\beta}^{n} - \boldsymbol{Q}_{\beta}^{n-1}}{\Delta t} - \sum_{k} \boldsymbol{u}_{k}^{n-1} \psi_{k}(\boldsymbol{Q}_{\beta}^{n-1}) \right) \right) dt + \frac{1}{\sigma^{2}} \hat{f}(\boldsymbol{Q}^{N}) \right)$$

Get symplectic Euler discretisation

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Can get higher-order methods by discretising the dynamical equation with a RK method; get a symplectic PRK method

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This gives a simple way of computing Jacobi information

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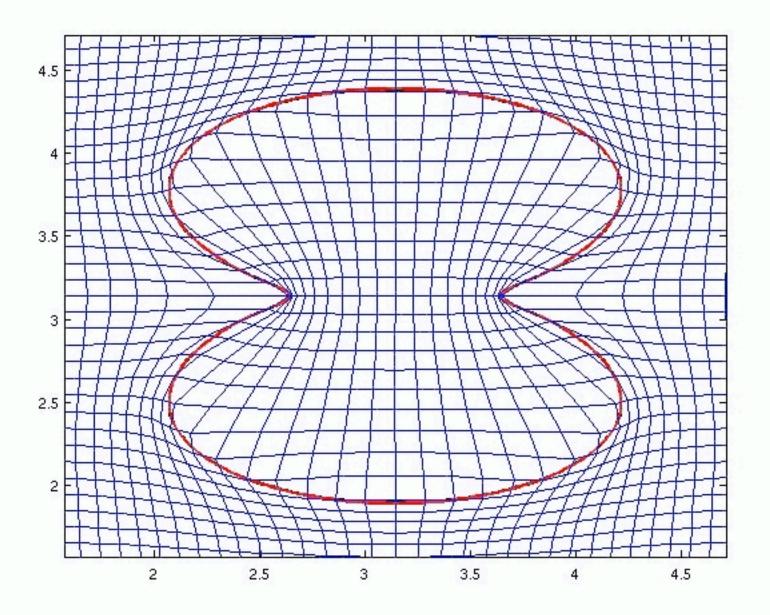
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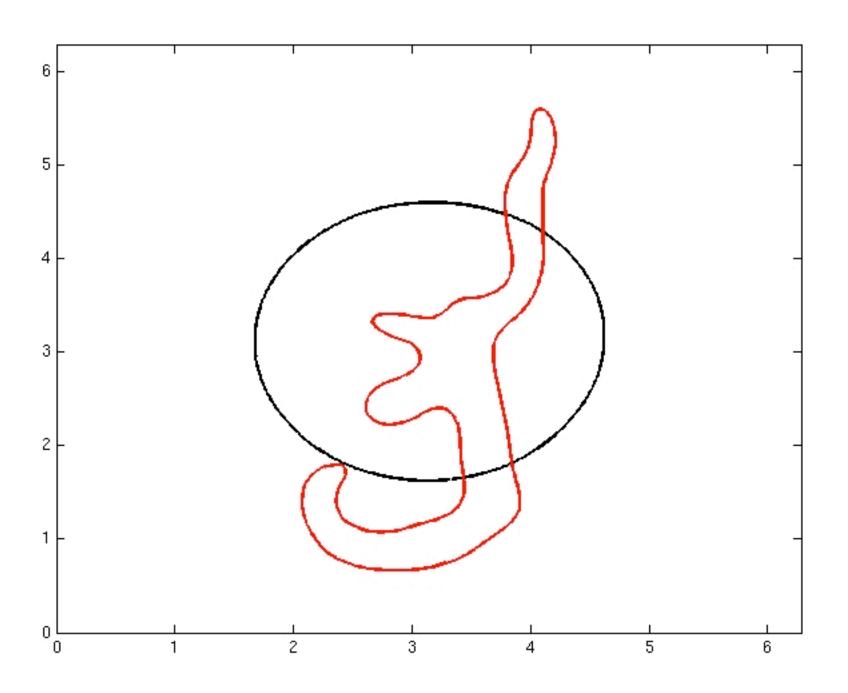
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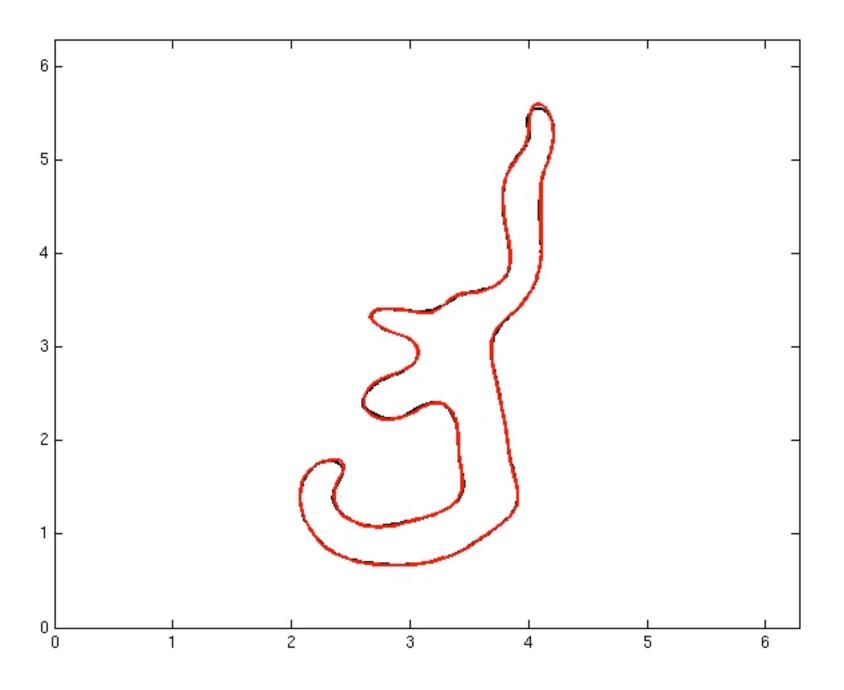
Extremise the discrete functional directly

Some movies

What does the shortest path between two shapes look like?







Summary

- * Variational shape matching is useful in a wide variety of applications: analysis of shape datasets and shape optimisation
- * Necessary when large deformations are needed
- * Shapes are embedded in a flow which follows geodesics in diffeomorphism group
- * Particle-mesh method gives simple discretisation with geometric properties for matching curves/surfaces

Outlook

- Collaborations with engineers at ICL and elsewhere
- Parallel algorithm for matching complex shapes
- Developing statistical analysis of shapes with Sofia Olhede (Maths, ICL→UCL)

The End