

More Shape Representations

- Currents
 - Representations via tangents
 - Deformetrica, using Currents
- Signed distance functions
 - NeRFs and visualizations via them

Curves in Deformetrica (Currents)



- J Glaunès, A Qiu, ML Miller, Younes. Large Deformation Diffeometric Metric Curve Mapping. IJCV, 2008.
- Distance between shape C and shape S

$$J_{C,S}((v_t)_{t\in[0,1]}) \doteq \gamma \int_0^1 \|v_t\|_V^2 dt + E(\phi_1^v \cdot C, S),$$

- Minimized via LDDMM
- Points with curve tangents
 - Better than point-to-point matching alone
 - Based on reproducing kernels
 - Works when data has noise

Curves in Deformetrica (Currents), 2

• Curve matching to an image **w** of vectors:

$$\langle \mu_C | w \rangle \doteq \int_0^1 \gamma'_C(s) \cdot w(\gamma_C(s)) ds,$$



- Via agreement of tangents of interrogated curve
- Captures both position and direction
- So matching curve C with curve S
 - $-\mu C|w$ difference metric to $\mu S|w$ small
 - What w? Extrapolation of the other
 - Based on reproducing kernels
 - Typically Gaussian
 - ?? Strong curvatures handled poorly

$$\int_0^1 \gamma'_S(s) \cdot w(\gamma_S(s)) \\ - \gamma'_C(s) \cdot w(\gamma_C(s)) \, ds.$$

Curves in Deformetrica (Currents), 3

• Curve positions and tangents matching to an image **w** of vectors:

$$\langle \mu_C | w \rangle \doteq \int_0^1 \gamma'_C(s) \cdot w(\gamma_C(s)) ds,$$



- Deform C to S $E(\phi(C), S) \doteq \|\mu_{\phi(C)} - \mu_S\|_{W^*}^2$ Win L DDMM producing value itigs
 - Via LDDMM, producing velocities
- Matching deformed curve C with curve S

 Via difference metric:

$$= \int_0^1 \gamma'_S(s) \cdot w(\gamma_S(s)) \qquad -\gamma'_C(s) \cdot w(\gamma_C(s)) \, ds.$$

- What **w**?
 - Based on reproducing kernels



Signed Distance Image (SDI) as Shape Representation

- Distance to boundary, with sign indicating interior vs. exterior
 - Boundary is zero level surface of SDI
 - Only really zero order, but related to Blum measures
 - Crossing problems in exterior
- Used in turning binary images of voxels into a boundary mesh (Marching Cubes)
- Used to produce boundary evolutions, incl. smoothings, that allow topological changes
- Used to produce Neural Radiance Functions (NeRFs), ~opacities, that can be used to produce boundary visualizations using Generative Neural Nets
 - Trained from sparse collection of poses



NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis,

Ben Mildenhall, Pratul Srinivasan, Matthew Tancik*, Jonathan Barron, Ravi Ramamoorthi, Ren Ng, ECCV 2020.