Matching Sparse Sets of Cardiac Image Cross-sections Using Large Deformation Diffeomorphic Metric Mapping Algorithm

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Introduction

- Cardiac disease is often associated with remodeling.
  - Ventricular shape and function is influenced by this remodeling.
  - Assessing left ventricular shape and motion at the population level requires establishing anatomical correspondence using registration based techniques.
  - Cardiac magnetic resonance imaging (MRI) provides detailed quantitative data about cardiac function and geometry.
  - Cardiac MRI data are sparsely sampled that is not optimum for intensity-based registration methods.
  - Methods that rely on fitting a smooth surface to the segmented contours may impose an artificial constraint to the registration process [1],[2].
- We propose:
  - to study the feasibility of matching sparsely sampled cardiac MR volumes using curve and surface matching in the context of large deformation diffeomorphic metric mapping [3],[4].

Preprocessing

- **Subjects:** Cardiac MR data from patients with familial cardiomyopathy (n = 5, 4 females, mean age of 50.4 ± 15.24 years). The in-plane resolution was approximately ∼1.4 mm × 1.4 mm and thickness was of 8 mm with 2 mm gap.
- **Segmentation:** Epi and endocardial contours of left ventricle (LV) were isolated using *Segment* [5] software.
- **Breath Hold Correction:** A 2D Euclidean distance-based matching approach was used to correct for breath-hold related slice to slice motion using contour points from 3 different perpendicular planes: short axis (SA), horizontal long axis (HLA), and vertical long axis (VLA).
- **Rigid aligment:** Before performing nonrigid matching, we roughly aligned and scaled the objects (curves and surfaces).
- **Template surfaces:** The template surface is a triangulation of a binary volume, that was obtained using shape averaging in a previous study [6] using intensity CT images from 25 subjects.

Registration Methods

- **Nonrigid Alignment between Segmentations**
  - Given two families of curves, $\Gamma^{(0)}$ and $\Gamma^{(1)}$ (with different number of points), we would like to find an optimal transformation, say ϕ, such that $\phi(\Gamma^{(0)}) \simeq \Gamma^{(1)}$ via minimizing the following objective function:

$$E(\Gamma,\alpha) = \int_0^1 F(\Gamma(t),\alpha(t))dt + \frac{1}{\sigma^2} D(\Gamma(1),\Gamma^{(1)})^2 \ . \tag{1}$$

The variables, Γ and α, are time dependent and the deformation cost function, F, is defined by:

$$F(\Gamma(t),\alpha(t)) = \sum_{k,l=1}^{N} \int\int \alpha_k(t,u)^T K(\gamma_k(t,u),\gamma_l(t,v))\alpha_l(t,v)dudv \ . \tag{2}$$

The matching term, D, is a Hilbert space norm [3] measuring the discrepancy between the deformed template curves ($\Gamma(1)$ at time $t = 1$) and target ($\Gamma^{(1)}$). $K(p,p')$ is a smoothing kernel function:

$$K(p,p') = \mathrm{diag}(g(\|p-p'\|), g(\|p-p'\|), g(z-z'))$$

with $g(t) = \exp(-t^2/2a^2)$ for some parameter a (where z and z' are the long-axis coordinates of p and p'). This ensures a uniform motion in the LV long axis direction.

- **Surface to curves registration**
  - Similarly in surface to curve registration we seek an optimal transformation that maps a closed surface $S^{(0)}$ to a collection of curves ($\Gamma^{(1)}$) via minimizing:

$$E(S,\alpha) = \int_0^1 F(S(t),\alpha(t))dt + \frac{1}{\sigma^2} D(S(1),\Gamma^{(1)})^2 \ . \tag{3}$$

The deformation cost is given by

$$F(S(t),\alpha(t)) = \int_{S^{(0)}}\int_{S^{(0)}} \alpha(t,p)^T K(S(t,p),S(t,q))\alpha(t,q)ds(p)ds(q) \ . \tag{4}$$

  - The kernel K is now chosen isotropic, such that $K(p,p') = g(\|p-p'\|)\mathrm{Id}_{\mathbb{R}^3}$ with g as above. The matching term, D, computes the sum of the integrals of the squared distances between each point in each curve in $\Gamma^{(1)}$ and the deformed surface $S(1)$.
- **Measure of robustness (Four experiments on 5 subjects)**
  - Matching high resolution template surface to complete target curve set.
  - Matching high resolution template surface to incomplete target curve set (removed one plane).
  - Matching complete curve set extracted from high resolution template data to complete target curve set (removed one plane).
  - Matching complete curve set extracted from high resolution template data to incomplete target curve set (removed one plane).

Results

- **Nonrigid Alignment of segmentations**

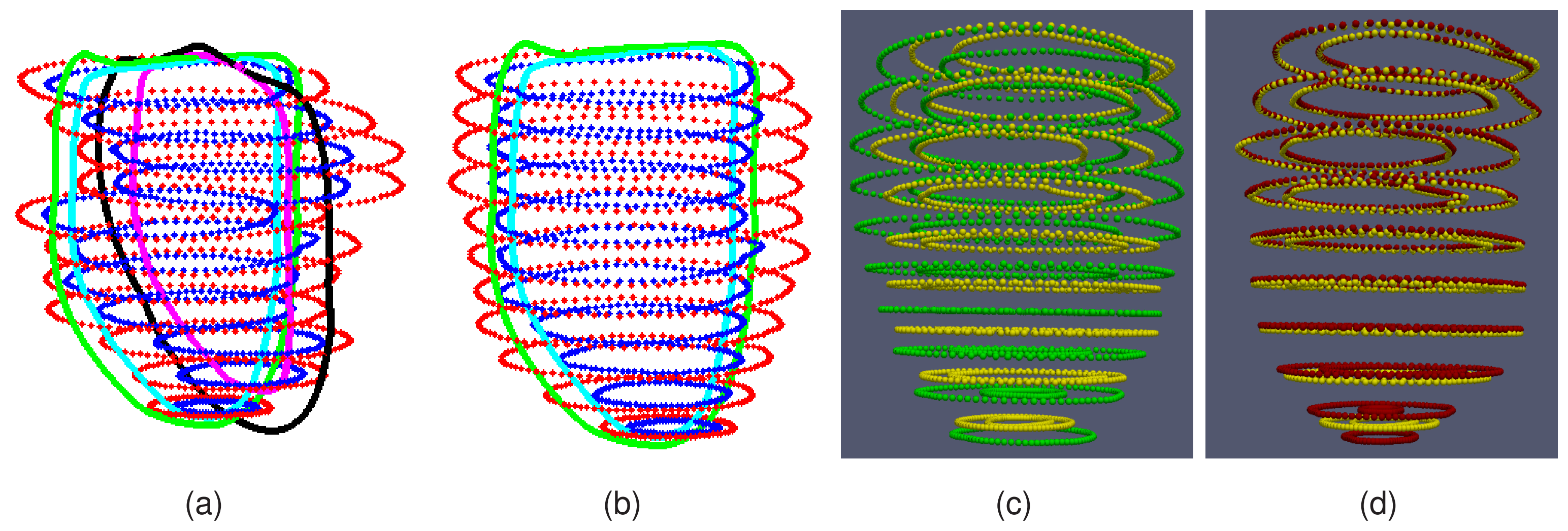

Figure: *(a-b)*: Correction of slice-to-slice misalignment in SA view due to breath-holding motion.*(a)*: Before correction. *(b)*: After correction. (Blue and red : endo and epicardial surfaces from SA view, Cyan and green: endo and epicardial contours from vertical long axis view, Pink and black: endo and epicardial contours from horizontal long axis view. *(c-d)* Curve-to-curve matching using LDDMM. *(c)*: LV contours before curve matching (green: template contours, yellow: target contours). *(d)*: LV contours after deforming template subject contours (red) to match target subject (yellow).

- **Nonrigid surface to curve registration**

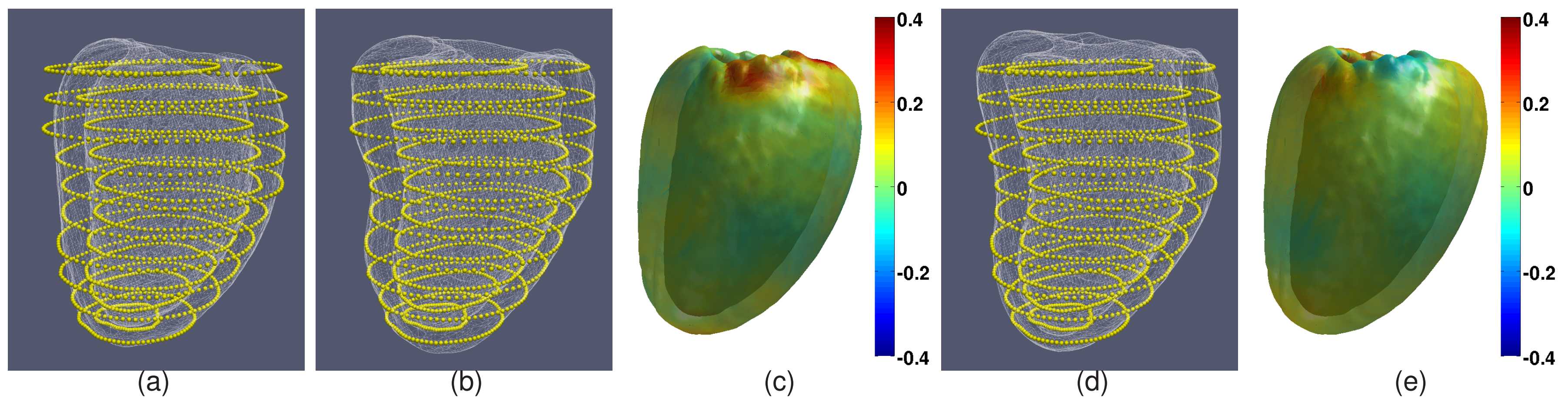

Figure: Surface-to-curve matching using distance-based LDDMM. *(a)*: Surface template with target contours. *(b)*: After registration.*(c)*: Map of the surface area ratio of triangulated faces in deformed template relative to template superimposed on template mesh (scale is based on log_{10}). *(d)*: After registration using projection of gradients on the first 24 eigenvectors of smoothing kernel. *(e)*: same as *(c)* but for the deformation estimated from *(d)*. Grey wireframe represents high resolution triangulated mesh template. Yellow contours are representing LV epi and endocardial regions from the MRI cross-sections.

- **Distance Error (mm)**
  - I) Matching high resolution surface to the complete curve set (distance between the removed cross-sectional curves to the deformed surface).
  - II) Matching high resolution surface template to the incomplete curve set (distance between the removed cross-sectional curves to the deformed surface).
  - III) Repeating case (I) with the curve to curve matching.
  - IV) Repeating case (II) with the curve to curve matching.
  - V) Pre-registration distance between the complete curve set and surface template.
  - VI) Surface to curve matching error estimated by using the entire curve set as opposed to using curves from a single cross section (case I)
  - VII) Curve to curve matching error estimated by the complete curve set

Experiments	I	II	III	IV	V	VI	VII
Mean(SD)	1.67(0.70)	2.79(0.80)	1.37(0.47)	4.31(1.71)	3.24(0.17)	1.75(0.29)	1.15(0.14)

Conclusions

- Surface to curve matching:
  - Does not rely on a predefined geometry.
  - Does not require same number of points for curves and surfaces.
  - Projection of gradient of objective function onto principal directions of smoothing kernel reduces the over-fitting problem.
- Curve to curve matching:
  - Does not require high resolution surface.
  - Sensitive to geometry coverage.
- Both approach are robust with respect to the missing data.

References

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