Title: Deformable Organ Contour Transfer with Deep Inverse Shape Encoding (DISE) Networks for Auto-segmentation in Low Contrast Regions

Innovation/Impact: Auto-segmentation in low contrast regions is challenging due to limited gradient information. The method investigated by this study is innovative in several aspects: (1) The concept and use of the inverse shapes are novel and have potential impact on image matching or mapping problems commonly seen in auto-segmentation. Conventional image mapping methods rely on numerical gradients, which quantify the change in function value in response to a small spatial displacement. Numerical gradients are sensitive to noise, artifacts presented in an image and become unreliable when there is a gross loss of structural and textural contents. In contrast, we probe the change in the spatial support in response to the change in function values. Specifically, we define the inverse shape of a small range $N_a$ of function values $\text{invShape}(N_a) = \{x|f(x) \in N_a\}$. It has the following properties. A member point in the inverse shape certainly has other member points in its neighborhood near and far. Two inverse shapes invShape($N_a$) and invShape($N_b$) do not overlap if and only if the two range sets $N_a$ and $N_b$ do not intersect. Thus, a range partition induces a dissection of the entire image domain into non-overlapping inverse shapes. 

![Figure 1](image1.png)

Figure 1: A dissection of the image domain into non-overlapping inverse shapes. Eight inverse shapes are shown, each is outlined by its boundary in a distinct color: (a) reference XCAT-CT image at respiratory phase I, and (b) target XCAT-CT at respiratory phase III [5].

The inverse shapes capture gradient information, local and global, by simple control of range partition. (2) In order to utilize the inverse shapes, we encode them in economic and robust representation, with DISE networks. (3) Instead of extending the deformable contour mapping problem to the dense deformable registration problem, we reduce it to the inverse shape mapping problem, to which we provide also robust and efficient solution with DISE networks. (4) DISE networks embody a coherent encoding-to-mapping scheme with key components: sparse sampling; sparse representation of intrinsic shape signatures, geometries in an extrinsic space and certain statistics; information propagation over network connections, driven by correlation metrics; and ultimately, rapid and reliable mappings between corresponding inverse shapes. We adopted state-of-art techniques for surface shape matching and morphing [11, 8], and we made necessary and innovative changes for volumetric mappings. (5) DISE networks can be applied to or facilitate other medical image processing and analysis tasks, such as segmentation, deformable registration, retrieval and graphics rendering.

Method Illustration and Experimental Results: We report our initial experimental investigation for proof of concept. We used anthropomorphic phantom XCAT-CT images created by Könik et al [5].

We present in Figure 2 input images: a reference CT image at respiratory phase I in (a) and a target image image at phase III in (b). The warped contour generated by our method for the target image is shown in (d). The transferred contour agrees very well with the ground truth, with the Dice coefficient greater than 0.97.

We illustrate in (a) of Figure 3 two sparsely sampled point sets, in red and blue, in two corresponding inverse shapes in the reference and target image domains, respectively. The associated range contains, not exclusively, the attenuation coefficient values for liver, the organ at risk. The anatomical structures in the inverse shapes are liver, diaphragms, aorta, and spleen. We show in (b) the samples (salient, non-shaded) that are correctly identified as in the liver region by the mapping our method found between the two images.

Two additional remarks. While our method with DISE networks proves successful with the particular XCAT-CT data, our earlier work on automatic contour transfer via texture-based segmentation and bipartite matching [6] is not applicable to the same data due to the absence of textures. A successful contour transfer via the cone-beam projection space will substantially enhance our LIVE system [9] for 2D-3D deformable registration, which is in clinical trial.

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\[ \text{invShape}(N_a) = \{x|f(x) \in N_a\} \]
Figure 2: Contour transferring between two XCAT CT volumes at respiratory phases I and III from [5]. (a) Reference CT with liver contour in blue, (b) Target CT in need of a liver contour, (c) Overlay of the reference and target images, (d) Target CT with warped liver contour, in red, generated by our method with DISE networks. Interpolation errors (not shown) from DISE sample points to XCAT control points are small.

Figure 3: Sparse samples, organ sample identification and contour comparisons: (a) red and blue samples in one pair of corresponding inverse shapes for the reference and target images, respectively, in two views; (b) liver samples identified in the target inverse shape, in two views; (c) 3D liver contours spanned by ground truth control points (top) and by identified liver samples (bottom), in two views. The Dice coefficient between the ground-truth and generated contours is greater than 0.97.

References