Deep Active Lesion Segmentation

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Motivation
Lesion segmentation is an important problem in computer assisted diagnosis that remains challenging due to the prevalence of low contrast, irregular boundaries that are unmanageable to shape priors. We introduce Deep Active Lesion Segmentation (DALS), which effectively leverages the strengths of CNNs and ACMs to create a fully automated segmentation framework.

Overview
The DALS framework benefits from:
- A novel multiscale encoder-decoder CNN that learns an initialization probability map \( \gamma_{\text{init}} \) and parameter maps for the ACM.
- An improved level-set ACM formulation with a per-pixel parameterized energy functional.

Figure 1: Segmentation comparison.

We evaluate our lesion segmentation model on a new Multilorgan Lesion Segmentation (MLS) dataset. Our results demonstrate favorable performance compared to competing methods, especially for small training datasets.

How Does it Work?
- An input image is fed into the encoder-decoder to localize the lesion and produce a segmentation probability map \( \gamma_{\text{seg}} \) that specifies the probability that any point \((x, y)\) lies in the interior of the lesion.
- The Transformer converts \( \gamma_{\text{seg}} \) to a Signed Distance Map, \( \gamma_{\text{SDM}} \), that initializes the level-set ACM and estimates the parameter functions \( \lambda_1(x, y) \) and \( \lambda_2(x, y) \) in the energy functional [1].
- During training, \( \gamma_{\text{seg}} \) and the ground truth map \( \gamma_{\text{gt}} \) are fed into a Dice loss function and the error is back-propagated accordingly.
- During inference, a forward pass through the framework produces a final SDM, which is converted back into a probability map, producing the final segmentation map \( \gamma_{\text{seg}} \).

Figure 2: The DALS framework: Multiscale encoder-decoder + Level Set ACM

How Does it Perform?
- Boundary Delineation: The DALS segmentation contours conform well to the irregular shapes of the lesion boundaries (Fig. 3), since the learned parameter maps, \( \lambda_1(x, y) \) and \( \lambda_2(x, y) \), provide flexibility to accommodate boundary irregularities. DALS performs well for different image characteristics, including low contrast and heterogeneous lesions.
- Parameter functions

Discussion

Results

Table 1: MLS Dataset statistics. GC: Global Contrast; GC: Global Heterogeneity

Table 2: Segmentation metrics for model evaluation. D denotes the confidence interval.

Table 3: Multiscale Encoder-Decoder With Parameter Functions

Figure 5: The contribution of the parameter functions was validated by comparing the DALS (a) against a manually initialized level-set ACM with scalar parameters (b). The learned maps \( \lambda_1(x, y) \) and \( \lambda_2(x, y) \) serve as an attention mechanism that provides additional degrees of freedom for the contour to adjust itself precisely to regions of interest.

Conclusion

The DALS framework includes a custom encoder-decoder that feeds a level-set ACM with per-pixel parameter functions. We evaluated our framework in the challenging task of lesion segmentation with a new dataset, MLS, which includes a variety of images of lesions of various sizes and textures in different organs acquired through multiple imaging modalities. Our results affirm the effectiveness of our DALS framework.