Ideal Seed Point Location Approximation for GrowCut Interactive Image Segmentation

Mario Amrehn[1], Maddalena Strumia[2], Stefan Steidl[1], Tim Horz[2], Markus Kowarschik[2], Andreas Maier[1,3]
[1]Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander University Erlangen-Nürnberg (FAU)
[2]Siemens Healthcare GmbH, Forchheim
[3]Erlangen Graduate School in Advanced Optical Technologies (SAOT)

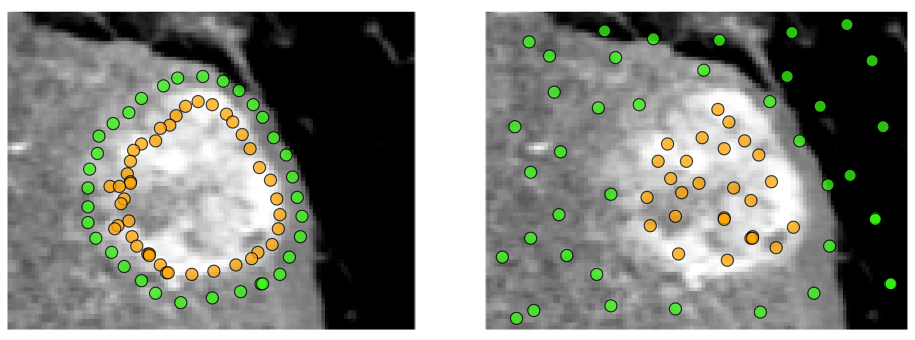
Intro. Methods

Interactive Lesion Segmentation

- C-arm CT X-ray is a common modality in medical imaging. After image formation, anatomical structures are extracted via segmentation.
- Interactive segmentation methods bear the advantage of a dynamically adjustable trade-off between time and achieved segmentation quality.
- A user interacts by drawing pictorial hints onto the acquired image via a graphical user interface. The quality of a segmentation varies substantially depending on the seed points' location in the image.

1. Seed Points GT Influence on Dice

Investigation of individual seed point locations' influence GT on the segmentation quality (Dice coefficient as figure of merit).



a) Surface seeds b) Volume seeds

- Moschidis et al. [1] exclusively analyzed seed importance by random sampling from categories a) and b).
- Seed importance **D** for whole input image is desirable to analyze shortcomings of a given segmentation technique.
- To generate $\boldsymbol{D}$, each possible new seed point location is exclusively added to the set of initial seed coordinates $\boldsymbol{X}_{\text{init}}$.
- The segmentation's Dice score $\boldsymbol{D}_{\mathbf{x}}$ for coordinate $\boldsymbol{x}$ is the quality of segmentation including seed point $\boldsymbol{x}$.

2. Seed Point Importance Prediction Framework

Proposition of an approximation framework for ideal seed placements using an extension of the GrowCut segmentation algorithm.

GrowCut [2] image segmentation defines an automaton as tuple $(\mathbf{G}_{\mathrm{I}}, \mathbf{Q}, \delta)$ with state set

$$\mathbf{Q} \ni \boldsymbol{Q}_e^t = \left((\boldsymbol{x}_e, \ell_e^t), \boldsymbol{\Theta}_e^t, \boldsymbol{c}_e, \boldsymbol{h}_e^t\right),$$

where ℓ is the label and $\boldsymbol{\Theta}_e^t$ is the strength of node e.

We propose an additional variable $\boldsymbol{h}_e^t$ as counter for accumulated label changes.

- Every node f, at each time step t, attempts to conquer its direct neighbors. If e is not conquered $\boldsymbol{Q}_e^{t+1} = \boldsymbol{Q}_e^t$, else
$$\boldsymbol{Q}_e^{t+1} = \left((\boldsymbol{x}_e, \ell_f^t), \boldsymbol{\Theta}_f^t \cdot \mathrm{g}(c_e, c_f), \boldsymbol{c}_e, \boldsymbol{h}_e^t + 1\right).$$
- $\boldsymbol{h}_{\mathbf{x}}^T$ approximate uncertainty of segmentation method. $\operatorname{argmax}_{\mathbf{x}} \boldsymbol{h'}_{\mathbf{x}}^T$ is chosen for a new seed,
- where $\boldsymbol{h'}^T$ is $\boldsymbol{h}^T$ filtered by a Gaussian kernel to reduce importance of single high values.

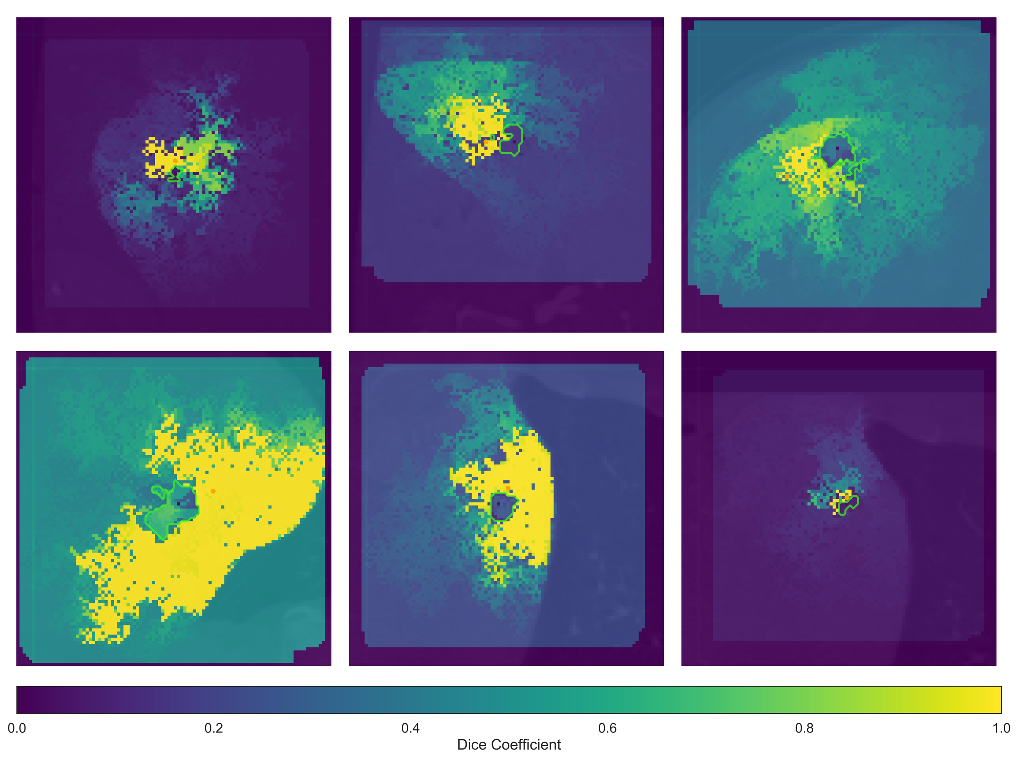
The area including the largest amount of label changes is preferred for seed location suggestion.

References

[1] E. Moschidis and J. Graham. In: *ISBI* (2010), pp. 928–931.
[2] V. Vezhnevets and V. Konouchine. In: *Graphicon* (2005), pp. 150–156.

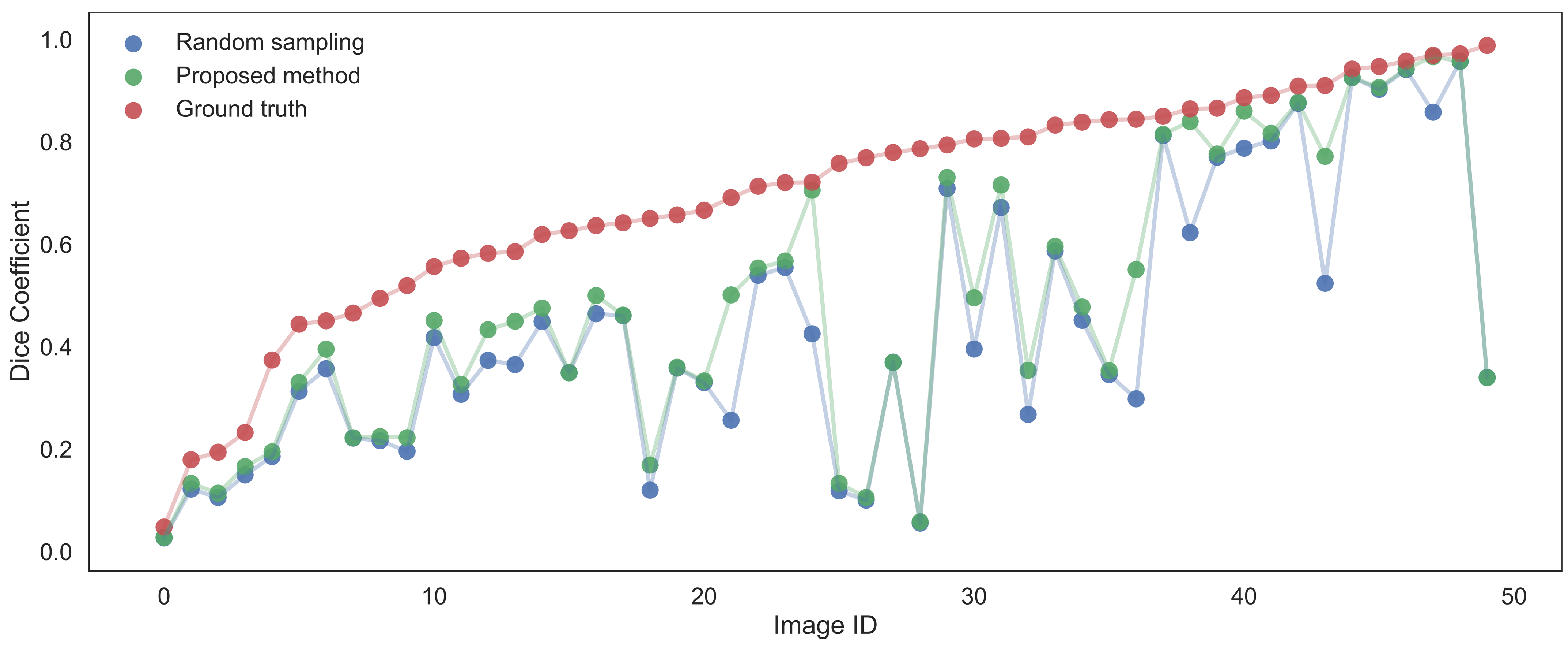
Evaluation

1. Ground Truth Influence Maps



GT seed location importance visualization.

2. Influence of Seed Location Selection on Segmentation Quality



Conclusions

- An extensive evaluation of the predictive power of seed importance was conducted from hepatic lesion input images.
- Our approach suggests seed points with a median of 72.5 % of the ideal seed points' associated Dice scores,
- which is an increase of 8.4 % points to sampling the seed location at random.

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https://www5.cs.fau.de/~amrehn, mario.amrehn@fau.de