

Ideal Seed Point Location Approximation for GrowCut Interactive Image Segmentation

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Abstract. The C-arm CT X-ray acquisition process is a common modality in medical imaging. After image formation, anatomical structures can be extracted via segmentation. Interactive segmentation methods bear the advantage of a dynamically adjustable trade-off between time and achieved segmentation quality for the object of interest w. r. t. fully automated approaches. The segmentation’s quality can be measured in terms of the Dice coefficient with the ground truth segmentation image. A user’s interaction traditionally consist of drawing pictorial hints on an overlay image to the acquired image data via a graphical user interface (UI). The quality of a segmentation utilizing a set of drawn seeds varies depending on the location of the seed points in the image. In this paper, we (1) investigate the influence of seed point location on segmentation quality and (2) propose an approximation framework for ideal seed placements utilizing an extension of the well established GrowCut segmentation algorithm and (3) introduce a user interface for the utilization of the suggested seed point locations. An extensive evaluation of the predictive power of seed importance is conducted from hepatic lesion input images. As a result, 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.

1 Introduction

The segmentation of hepatocellular carcinoma (HCC) in C-arm based computed tomography (CT) images is of vital importance for the trans-catheter arterial chemoembolization (TACE) [1] procedure. A more accurate segmentation of the tumor increases the treatment’s efficacy while minimizing the toxicity for surrounding healthy tissue during treatment with chemotherapeutic agents. Contrast enhanced tumors appear as inhomogeneous hyper dense or hypo dense proliferations in the radiographic projections. A tumor represented by non-homogeneous attenuation values considerably impedes an exact distinction between cancerous cells and their surrounding healthy hepatic tissue. Due to this

high variability interactive segmentation methods are superior to fully automatic segmentation approaches to obtain exact segmentations of HCC during TACE.

An interactive segmentation method may require a large amount of user interaction. The aim of this work is to reduce the user’s assistance to a minimum in order to increase the efficiency of the overall segmentation process. This is realized via an automatic preselection of the seed point locations.

2 Materials and Methods

2.1 Evaluation Method for Seed Importance

Moschidis et al. [2] investigated the varying importance of sets of seed points for interactive segmentation processes incorporating pictorial hints from a user w. r. t. the resulting segmentation’s quality. They concluded that seeds placed exclusively near the actual contour line of the object yield inferior segmentation results than seeds spread over the whole image space. Both alternatives are depicted in Fig. 1. Moschidis et al. exclusively analyzed seed importance by selecting seed locations sampled at random from each of the two provided categories. However, a full image of seed importance $\mathbf{D} \in \mathbb{R}^{w,h}$ with the same resolution as the 2-D input image $\mathbf{I} \in \mathbb{R}^{w,h}$ itself is desirable in order to analyze shortcomings of a given segmentation technique for each input element $\mathbf{I}_{\mathbf{x}}$, where $\mathbf{x} \in \mathbb{R}^2$.

In this paper, to generate a full image of seed importance \mathbf{D} , at each coordinate \mathbf{x} for a possible new seed point (i. e. $\mathbf{x} \notin \mathbf{X}$), this seed’s location is exclusively added to the set of initial seed coordinates $\mathbf{X} \ni \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$, with $n \ll w \cdot h$ for a single segmentation. The segmentation’s Dice coefficient $\mathbf{D}_{\mathbf{x}}$ for image coordinate \mathbf{x} can be interpreted as the quality of the segmentation including seed point \mathbf{x} . Since the segmentation’s Dice value without the current seed point (i. e. just from the initial seeds) is the same for all non-initial seed point locations $\mathbf{x} \notin \mathbf{X}$, the resulting image of Dice values can be interpreted as an image of seed location importance for the current segmentation task. Such an image transformation into the domain of a figure of merit for seed location

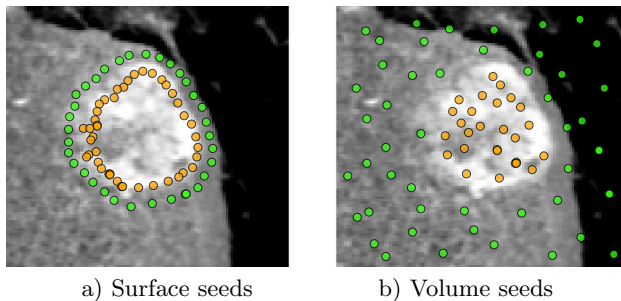


Fig. 1. Illustration of the two seeding categories (a, b) defined by Moschidis et al. [2]. Foreground seed locations depicted in orange. Background seeds depicted in green.

importance evaluation involves $w \cdot h - n$ separate segmentation operations for each input image. For an objective image of seed importance $\mathbf{D}_{\mathbf{x} \in \mathbf{X}} \lesssim \mathbf{D}_{\mathbf{x} \notin \mathbf{X}}$.

2.2 Seed Location Impact Approximation

The GrowCut [3,4] algorithm for image segmentation is based on cellular automaton theory. An automaton is defined by the tuple $(\mathbf{G}_I, \mathbf{Q}, \delta)$. \mathbf{G}_I is the graph of image \mathbf{I} , where image elements are nodes \mathbf{v}_e with associated image value \mathbf{c}_e . Nodes are connected by the Moore neighborhood system. The state set \mathbf{Q} consists of $\mathbf{Q}_e^t = ((\mathbf{x}_e, \ell_e^t), \Theta_e^t, \mathbf{c}_e, \mathbf{h}_e^t)$, where ℓ is the seed label and Θ_e^t is the strength of node e at iteration t . We propose an additional variable \mathbf{h}_e^t as counter for accumulated label changes of e during the GrowCut iteration, where $\mathbf{h}_e^0 = 0$. Θ_e^0 is 1 for initial seed locations \mathbf{X} , and 0 otherwise. State transitions (iterations) $\delta(\mathbf{Q}_e^t) = \mathbf{Q}_e^{t+1}$ are performed utilizing δ : start from initial seeds. Propagate labels w. r. t. local intensity features \mathbf{c} . every node f , at each time step t , attempts to conquer its direct neighbors. Node e is conquered if $\Theta_f^t \cdot g(\mathbf{c}_e, \mathbf{c}_f) > \Theta_e^t$, where $g(\mathbf{c}_e, \mathbf{c}_f) = 1 - \|\mathbf{c}_e - \mathbf{c}_f\|_2 / (\max_{j,k} \|\mathbf{c}_j - \mathbf{c}_k\|_2)$. If e is conquered, $\mathbf{Q}_e^{t+1} = ((\mathbf{p}_e, \ell_f^t), \Theta_f^t \cdot g(\mathbf{c}_e, \mathbf{c}_f), \mathbf{c}_e, \mathbf{h}_e^t + 1)$, else $\mathbf{Q}_e^{t+1} = \mathbf{Q}_e^t$. The bounded node strengths are monotonously decreasing. The process is guaranteed to converge. The values of $\mathbf{h}_\mathbf{x}^T$, where T is the final iteration, are used to approximate the uncertainty of the segmentation method w. r. t. each seed location in input image $\mathbf{I}_\mathbf{x}$. The index associated with the highest number of label changes $\text{argmax}_\mathbf{x} \mathbf{h}'_\mathbf{x}{}^T$ is selected as most important location for an additional seed, since a minimization of the algorithms uncertainty during segmentation is synonymous with a fast convergence of the interactive segmentation's contour line outcome towards the ground truth segmentation. \mathbf{h}'^T is \mathbf{h}^T filtered by a Gaussian kernel with standard deviation σ . Utilizing \mathbf{h}'^T instead of \mathbf{h}^T reduces the importance of single high values which increases the approximation quality of the system. Using \mathbf{h}'^T , the area including the largest amount of label changes is preferred for seed location suggestion.

2.3 Interactive Application

We utilize a UI including the described suggestion of relevant seed locations into the workflow of interactive segmentation. As depicted in Fig. 2, the UI presents two seed point locations to the user for interaction as proposed in [5]. They decide, which of the four possible variations of foreground and background labels to assign to these seed locations. Exactly one of the four represents the correct labeling. In order to assist the decision process, implicit changes to the contour line consequential to the labeling are displayed by highlighting label changing areas on the four overlay images on the right. After selection the two seed locations are added to \mathbf{X} . The user is presented two subsequent seed locations and interacts with the system until they are satisfied with the segmentation result. The process for determining the locations of the two seeds is an iterated version of the one described in Sec. 2.2, where after the first location suggestion \mathbf{x}_s , another seed is suggested with $\mathbf{X} = \mathbf{X} \cup \{\mathbf{x}_s\}$ as initial seed locations.

3 Experiments

For an evaluation the full map of seed importance \mathbf{D} using the Dice score as a figure of merit is computed for 50 2-D lesion images acquired by a C-arm CT scanner. Ground truth of the tumor outlines was generated manually by medical experts. The segmentation is performed via the GrowCut method. Initial background seeds are provided along the edges of the region of interest (ROI) of fixed 100 pixels in width w and height h . At least a single initial seed is required for each class label using GrowCut. Therefore, \mathbf{X} consists of these background seed locations as well as the coordinate of a single foreground seed, which is determined by the center of mass of the lesion’s binary ground truth segmentation. $\sigma = 5$ is selected after initial experimentation. Subsequent to the generation of \mathbf{D} , which is outlined in Sec. 2.1, the approximation results utilizing the method proposed in Sec. 2.2 are evaluated with \mathbf{D} as ground truth.

4 Results

The influence of a seed’s location on the overall segmentation outcome is shown in Fig. 4 via the ground truth image \mathbf{D} generated as described in Sec. 2.1. The evaluation of the seed location suggestion approach is depicted in Tab. 1. A detailed illustration of the achieved segmentation quality per input image is given in Fig. 3.

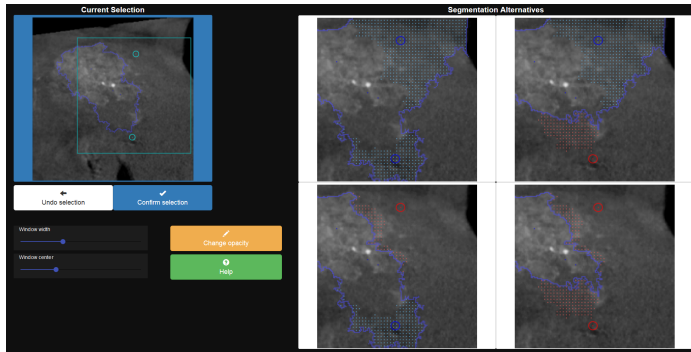


Fig. 2. The proposed application’s UI for the seed point approximation method consists of four buttons to select groups of seed points generated by seed location importance approximation. The user is asked to select the correct labels for the two chosen seed locations. Background seeds are depicted in red, foreground seeds in blue. On the left, the zoomed in region and seed locations are highlighted for improved user orientation. The dotted areas illustrate the difference in each of the four possible next segmentation outlines w. r. t. the previous iteration’s outline.

Table 1. Ideal seeds from \mathbf{D} which provide the maximum achievable Dice score as reference for the seed location suggestion methods are depicted in the first column. Results of the proposed seed location suggestion approach are displayed in the second column. A baseline to the proposed method is provided by random sampling of seed locations as depicted in column three.

Dice score	Ideal seeds from \mathbf{D} i. e. reference for 100 %	Proposed method’s result relative to ideal seeds’ Dice value	Random seed location sampling
Mean	0.696	68.5 % (i. e. +6.2 % points)	62.3 %
Median	0.758	72.5 % (i. e. +8.4 % points)	64.1 %
Std	0.221	24.1 % (i. e. +0.4 % points)	23.7 %

5 Discussion and Outlook

As depicted in Fig. 4, Moschidis et al. [2] drastically simplified the distribution of seed location importance by implying that seeds from one of the two categories are inherently superior to the other. The proposed method for seed location suggestion yields superior results in comparison to the random sampling baseline as shown in Tab. 1 and Fig. 3. The maximum achievable Dice coefficient varies depending on the input image (Fig. 3). Further studies might investigate which patterns in the input image result in a low maximum Dice value in the seed location ground truth. Related to this, the influence of image scaling might be worth investigating to reduce the computation time during evaluation (Sec. 2.1) as well as approximation (Sec. 2.2). Similar evaluations utilizing other seeding segmentation approaches than GrowCut would be of interest.

Disclaimer: The concept and software presented in this paper are based on research and are not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

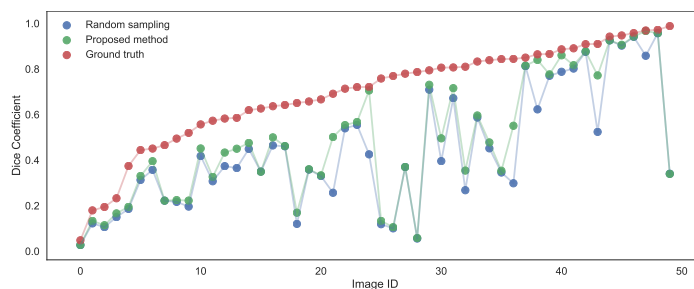


Fig. 3. Comparison of selected seed locations’ influence on the Dice score. The points in red mark the maximum achievable Dice score when adding just one more seed point with coordinates \mathbf{x} to an initial set of seed points \mathbf{X} . The achieved Dice score by the proposed method’s suggested seed location is depicted in green. A baseline suggestion is illustrated in blue. Images are sorted by their maximum achievable Dice score with one added seed point.

References

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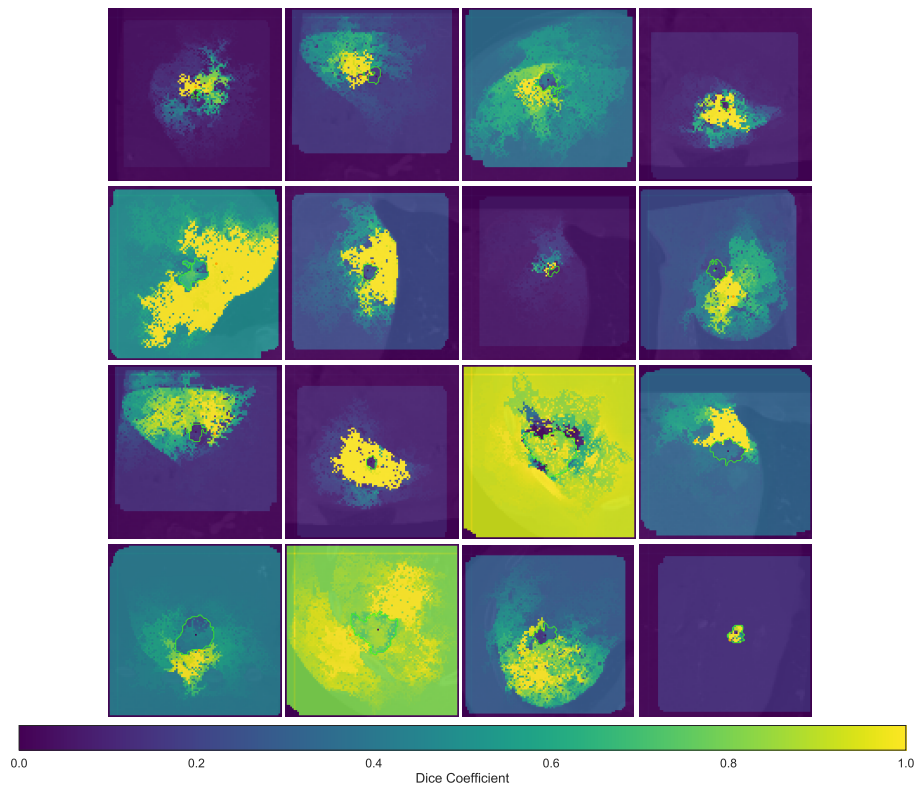


Fig. 4. Selected results from seed location ground truth generation (Sec. 2.1) displayed as an overlay on top of each gray-valued input image. The segmentation ground truth contour line is depicted in green. The orange dot highlights the coordinate of most important / influential seed point. Dark purple indicates initial seed point locations.