Robust Seed Mask Generation for Interactive Image Segmentation

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Abstract

In interactive medical image segmentation, anatomical structures are extracted from reconstructed volumetric images. The first iterations of user interaction traditionally consist of drawing pictorial hints as an initial estimate of the object to extract. Only after this first phase, the efficient selective refinement of current segmentation results begins. Erroneously labeled seeds, especially near the border of the object, are challenging to detect and replace for a human and may substantially impact the overall segmentation quality. We propose an automatic seeding pipeline as well as a configuration based on saliency recognition, in order to skip the time-consuming initial interaction phase during segmentation. A median Dice score of 68.22% is reached before the first user interaction on the test data set with an error rate in seeding of only 0.088%.

Index Terms—Interactive Image Segmentation; Seeding; HCI; Usability; Interaction; Segmentation; Medical Imaging.

I. INTRODUCTION

SEGMENTATION is a fundamental part of semantic image analysis. During segmentation, each image element is mapped to one of $N$ pre-defined class labels. In medical image processing, two-class problems ($N := 2$) are among the most common use-cases for image segmentation. Here, significant objects, often coherent anatomical structures like liver tumors (HCC), are extracted from image background based on local image features. Interactive image segmentation provides a good trade-off between the accuracy of manual segmentation and the speed and scalability of automatic segmentation techniques. In a cooperative human computer interaction (HCI) workflow, the current segmentation result’s similarity to the desired object boundary is improved iteratively. The user incrementally adds pictorial hints to the seed mask, which, in addition to the volumetric image, is utilized as the input for the segmentation technique. After each additional hint, the computation of the next segmentation result is started, until a user-defined stopping criterion is reached.

Popular workflows like [1]–[3] start the interactive process without any prior seed mask. Several usability studies [4]–[6] illustrate, that users spend significant amounts of time and effort in the beginning of the interactive workflow to achieve segmentation accuracies which would also be reachable by fully automated systems [7]. Only after this first phase, an interactive approach can outperform other segmentation techniques. Utilizing standard automated segmentation for a generic seed selection step prior to user defined seeding is challenging, since most seeded segmentation techniques require a truthful labeling of all input seed points. Given invalid labels, the ground truth segmentation may not be reachable even if the user is not restricted on time or number of interactions for the further process. An ideal pre-seeding technique therefore, (1) automates the task of initial seed placement, maximizing the initial segmentation’s quality, while (2) minimizing the error of falsely defined object labels. Such seeding methods, embedded in a common pipeline framework, are proposed and evaluated in this paper.

II. MATERIALS AND METHODS

The proposed workflow for automated seeding consists of four procedural steps $(P, S, W, M)$, as depicted in Fig. 1. Image pre-processing $P$ is performed by bilateral filtering. Seeding $S$ is performed separately for foreground (FG) seeds and background (BG) seeds. Given an object which is in its entirety inside the image volume, valid BG seeds can simply be generated along the border of the volume. For FG seeding, we focus on three types of methods: Otsu thresholding $S_o$ [8], Gaussian mixture model (GMM) based segmentation $S_g$, and binarized saliency detection $S_{(r,t,m,f)}$.

For $S_g$, a GMM is trained on the intensity values of the current image. Subsequently, the Gaussian best describing FG seeds is select by comparing the median intensities of image
elements which associated probability density function (PDF) value is above a certain threshold. The Gaussian distribution
with maximal median value is chosen for FG seed generation. The mean of the maximum and median values of the PDF are
then utilized as threshold for a binarization of the probability map.

The goal of saliency detection is to emphasize and outline
the largest salient object in the volumetric image, while
disregarding high frequencies which may arise from noise and
texture artifacts. Four popular saliency methods are compared:
$S_r$ [9], based on connectivity quantization as a boundary prior
for robust background detection, frequency-tuned detection
$S_f$ [10], a minimum barrier detection $S_m$ [11], and saliency
filters $S_{\ell}$ [12] utilizing low-level image features like contrast.
Binarization is performed by Otsu thresholding of the 10\%
largest saliency scores per image.

Seeds are weighted $W$ by a Gaussian kernel, shifted to the
center of mass of the current seed mask. Weights for non-seed
image elements are set to zero. Morphological post-processing
is conducted by binary opening $M_o$, binary erosion $M_e$, or
omitted. For the evaluation, a segmentation is performed on
the seeds via RandomWalker (RW) [3] and GrowCut (GC)
[2], [13]. For GC, the weighted seed mask is utilized as the
strength map. An evaluation is conducted utilizing 28 fully
annotated volumetric HCC data sets.

III. RESULTS AND DISCUSSION

Qualitative results of the saliency binarization phase are
depicted in Fig. 3. Here, only $S_m$ produces an invalid FG
seed, which, however, is eliminated during the subsequent
post-processing $M$. The segmentations via GC and RW, which
are based on the automated pre-seeding, are depicted in Fig. 2.
Method ($P$, $S_m$, $W$, $M_e$) achieves the highest median Dice
score for GC segmentation. ($P$, $S_m$, $W$, $M_e$) median Dice
score for RW is 93.4\% of the maximal score reached by
($P$, $S_r$, $W$, $M_e$), however, yields more robust results due to
26.2\% reduced standard deviation. The FPR of the generated
seeds w.r.t. the ground truth are depicted in Fig. 4

IV. CONCLUSION

An automated seeding pipeline was defined and evaluated,
which supports various saliency detection based as well as

![Figure 2](image-url)
Figure 2. Evaluation of GC (left) and RW (right) segmentations’ Dice scores. Proposed method ($P$, $S_m$, $W$, $M_e$) is highlighted by $\star$.

![Figure 3](image-url)
Figure 3. Saliency maps (upper row) from input image (upper left) utilizing different detection techniques $S_{(r,t,f,m)}$. Seed masks (lower row) are obtained via thresholding. Ground truth object contour line depicted in green.

![Figure 4](image-url)
Figure 4. False negative rate (FNR) of object seed points. Mean FNR medians per method: 0.09 \% ($S_m$), 0.10 \% ($S_f$), 0.16 \% ($S_r$), 0.23 \% ($S_t$), 0.30 \% ($S_{\ell}$).
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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.

APPENDIX A

Figure 5. Selected results: saliency maps (upper rows) from input image (leftmost column) utilizing different detection techniques $S_{r,t,m,f}$. Seed masks (lower rows) are obtained via thresholding and weighting. The annotated contour lines of the ground truth segmentation are depicted in green.