

# Smart Paint

## – A New Interactive Segmentation Method Applied to MR Prostate Segmentation

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**Abstract.** This paper describes a general method for interactive segmentation, *Smart Paint*. The user interaction is inspired by the way an airbrush is used, objects are segmented by "sweeping" with the mouse cursor in the image. The user adds or removes details in 3D by the proposed segmentation tool and the user interface shows the segmentation result in 2D slices through the object. We use the novel method for prostate segmentation in transversal T2-weighted MR images from multiple centers and vendors and with differences in scanning protocol. The method was evaluated on the training set obtained from <http://promise12.grand-challenge.org>. In the first round, all 50 volumes were segmented and the mean of Dice's coefficient was 0.82 with standard deviation 0.09. In a second round, the first 30 volumes were re-segmented by the same user and the result was slightly improved – Dice's coefficient  $0.86 \pm 0.05$  was obtained. For the training data, the mean time to segment a volume was 3 minutes and 30 seconds.

The proposed method is a generic tool for interactive image segmentation and this paper illustrates that it is well-suited for prostate segmentation.

## 1 Background

Segmentation is an essential step in many situations in medical image based diagnosis and treatment planning tasks. Usually it is impossible to do a fully automated segmentation with sufficient accuracy, at least without having organ specific models. Therefore various semi-automatic or interactive approaches are used. However, performing interactive segmentation of 3D image volumes slice by slice is tedious and time consuming. The challenge then is to create tools that allow interaction in 3D in an effective way.

We have been active in the field of interactive segmentation for several years and have developed methods and the theory for, e.g., graph-based image processing tools [1,2,3]. We have also produced a general 3D image visualization and segmentation toolbox called Wish [4], available on <http://www.cb.uu.se/research/haptics/>. Wish uses stereoscopic displays, 3D interaction devices and

haptics to allow natural interaction in 3D. This works very well but of course limits the general applicability of the solutions on general purpose computers.

In general, an interactive segmentation method should fulfill a number of criteria to be of practical use, [5]:

1. The method should be intuitive for interaction and the segmentation method should allow the user to provide precise characterizations of what the segmentation method should do and the segmentation method should be transparent for a user to be able to give correct user input.
2. The method should be highly efficient and run at interactive speed, meaning in practise linear time in the number of image elements with low constant factors. It should also be fast to update a segmentation when new user input is added.
3. The method should be able to capture important groupings or regions.

Recently, we developed a new segmentation tool that can be used effectively on a general purpose computer with a normal 2D display and a computer mouse for the interaction while still working fully in 3D in the image volume. We call this new tool Smart Paint – the user improves the segmentation by sweeping with the mouse cursor in the object or background, similar to how an airbrush is used. Areas are painted with a semi-transparent color which gives immediate feed-back in the chosen interaction plane. But if the user moves to another plane using the mouse-thumbwheel the effect of the painting is seen also there. The very special feature of this tool is that the paint seems to understand where you want to apply it, it usually selectively sticks to the organ of interest while avoiding other structures, therefore the word "smart" in the name of the tool.

The "magic" behind this behavior is that the algorithm takes both the Euclidean distance to the mouse cursor and the image content (intensity values) into account. Each voxel has a certain probability of belonging to the foreground and the background. This probability can be incremented or decremented when the brush passes in the vicinity of the voxel, how much depends on its spatial and intensity distance from the brush centre. When the probability passes a threshold, typically 0.5, it is switched from background to foreground or vice-versa. This simple concept is remarkably efficient in practice.

The feedback loop between the user and the updated segmentation is very efficient in the proposed method. The segmentation is updated as soon as the user moves the mouse cursor and the feed-back to the user is immediate.

When we learned about the PROMISE12 challenge we decided that it provided an excellent frame-work for evaluating our new segmentation tool. We do believe that organ specific, model based segmentation approaches have an important role in medical image analysis and we are actually in the process of starting a project on prostate image analysis together with our partners at the Dept. of Radiology, Uppsala University. So perhaps we will have more automatic tools to evaluate in a future challenge. Still our initial experiences from using Smart Paint were so encouraging that we wanted to try it in this very challenging context.

A recent survey of methods for segmentation of the prostate is found in [6]. Many different methods have been proposed based on, for example, extracting salient edges, Active Contour Models (ACM), Active Shape Models (ASM), shape priors assuming that the prostate is shaped as an ellipsoid, etc. Most of the methods are developed for segmentation of 2D slices.

In this paper, we describe the algorithms behind Smart Paint and our initial experiences from applying it to prostate segmentation. How accurate this method turned out to be in comparison to other more problem specific approaches will be an interesting outcome from the evaluation in the PROMISE12 challenge.

## 2 Methodology

### 2.1 Representation

The image  $I$  and the segmentation function  $f$  are mappings from elements of a three-dimensional voxel set to the interval  $[0, 1]$ . A voxel  $x$  belongs to the *foreground* if  $f(x) \geq 0.5$ , and to the *background* otherwise.

### 2.2 Painting

Initially,  $f \equiv 0$ . The brush tool has a value  $v$  that is either one (to increase the foreground) or zero (to increase the background). A single brush stroke at voxel  $x$  affects the segmentation according to

$$f(y) \leftarrow \alpha(x, y)f(y) + (1 - \alpha(x, y))v, \quad (1)$$

where  $\alpha$ , a function of the coordinates of the two voxels  $x, y$  and two constants  $k$  and  $\beta$ , is given by

$$\alpha(x, y) = \beta |I(y) - I(x)|^k \max(r - d(x, y), 0), \quad (2)$$

where  $d(x, y)$  is the Euclidean distance between the voxel centers of  $x$  and  $y$ ,  $r$  is the brush radius specified by the user and  $\beta$  and  $k$  are constants. The algorithm is not very sensitive to the choice parameters, we used values of  $\beta$  in the range  $[0.01, 0.1]$  and  $k = 3 \pm 2$ .

### 2.3 Smoothing

A smoothing step is often needed since the obtained segmentation can be a bit jagged. The neighborhood of a voxel  $x$ ,  $\mathcal{N}(x)$  is the set of voxels that are adjacent to  $x$ . Here we use the 6-neighborhood, i.e., voxels are adjacent if they differ by one in only one coordinate. Smoothing is performed by replacing the value of  $f(x)$  at each voxel by a weighted average of the values at the neighbors:

$$f(x) = \frac{\sum_{y \in \mathcal{N}(x)} \frac{(1 - |I(x) - I(y)|)^k}{1 + d(x, y)} f(y)}{\sum_{y \in \mathcal{N}(x)} \frac{(1 - |I(x) - I(y)|)^k}{1 + d(x, y)}}$$

### 3 Experimental Design

Since Smart Paint is a fully interactive tool without any built in application knowledge the result will be highly dependent on the operator. You could expect different results if you trained an expert on prostate MRI based diagnosis in using Smart Paint or trained an image analysis expert on MRI based prostate anatomy. We took the latter approach, one of us with many years of image analysis experience took a one hour crash course on prostate anatomy as seen in MRI images given by experts at the Dept. of Radiology, Uppsala University and then started practicing on the provided training data. We spent in total a bit less than a working day on the training and for segmenting all the training cases, about half of them twice.

The experiences were that the tool worked very well but there were sometimes difficulties in visually knowing where the borders were supposed to be. The resulting segmentations were evaluated using one of the suggested metrics, as documented in the next section. Then the same method was applied to the test set and the resulting segmentations have been submitted for evaluation by the organizers.

#### 3.1 User Interaction

The method heavily depends on interaction from the user. These are the main steps the user performed when segmenting the prostate:

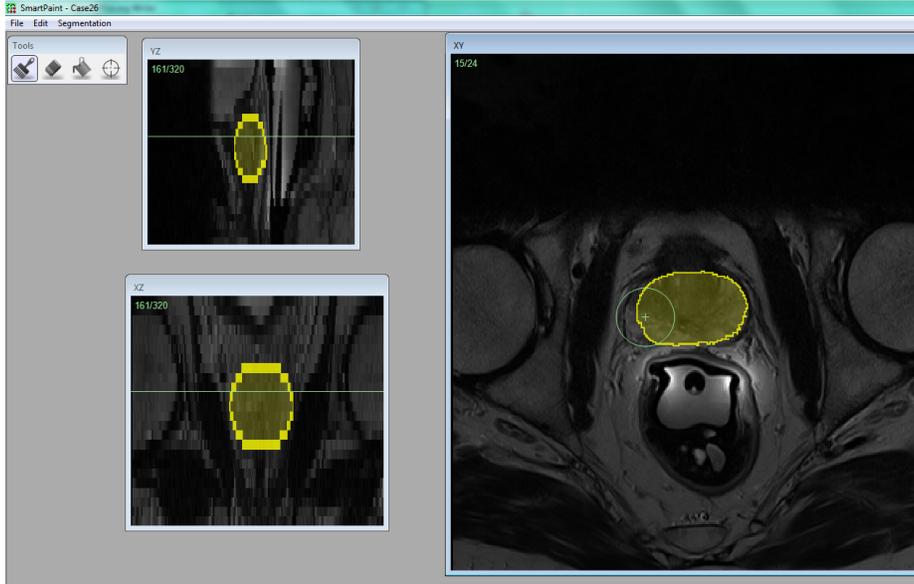
1. Move your cursor around inside the prostate in a fairly centrally located slice and paint it by pushing the left mouse button. The paint will mainly stick to prostate tissue. If needed you can remove paint by pushing the right mouse button.
2. Scroll to other slices using the mouse wheel and apply/remove additional paint as needed. The paint layer can be turned on/off by the space bar.
3. The size of the brush can be changed using ctrl-mouse wheel. Typically you start with the default, rather large brush and shrink it towards the end when you need to fine adjust borders.
4. If the shape is very irregular in the third dimension you can switch to 2D paint mode, but that is rarely needed.
5. You can optionally smooth the resulting boundary by a 3x3x3 operator by pushing ctrl-A.

The user interface of the method is illustrated in Figure 1.

### 4 Results and Discussion

#### 4.1 Quantitative Results

As a quantitative measure of the difference between the obtained segmentations and the ground truth, Dice's coefficient is used. Dice's coefficient is a similarity



**Fig. 1.** User interface (cropped). The user sets the radius and sweeps the marker (the disk defined by the radius centered by the mouse cursor is shown as a green circle). The outer contour is highlighted and the overlaid segmentation can easily be toggled on/off.

measure over two sets  $X$  and  $Y$  defined as

$$D = \frac{2|X \cap Y|}{|X| + |Y|}.$$

Here,  $X$  and  $Y$  is the set of object voxels (coordinates) obtained by the proposed method and the ground truth, respectively.

All 50 volumes in the training data were segmented by the Smart Paint-method in a first round, and 30 of the volumes were segmented in a second round. The mean, standard deviation and median of Dice's coefficient were computed by comparing the obtained result with the ground truth available on the PROMISE12 homepage. In Table 1, the mean, median and standard deviation for the segmentation result of (i) all 50 volumes in round 1, (ii) volumes 00-29 in round 1 and (iii) volumes 00-29 in round 2.

## 4.2 Efficiency

**Implementation Details** The implementation details are shown in Table 2.

**Runtime** Since the segmentation approach was fully interactive with our new general purpose segmentation tool Smart Paint the segmentation times will of

**Table 1.** Dice’s coefficient of segmentation result of the available training data compared to the ground truth available on the PROMISE12 homepage.

Data set	mean	median	standard deviation
The full training set, round 1	0.8222	0.8486	0.0875
Volumes 00-29 of the training set, round 1	0.8109	0.8450	0.1060
Volumes 00-29 of the training set, round 2	0.8579	0.8566	0.0484

course depend on how fast the operator works. What specific hardware that was used is not crucial, since updating the segmentation by the smart paint-tool is done in as good as real time on any reasonable fast modern computer.

Our average for the training data was 3 minutes 30 seconds per volume in the training data with a maximum time of 5 min 30 seconds and a minimum of 2 minutes. The experience was that you can do a rather good segmentation in about 30 seconds, then it takes a few minutes to go through it and adjust the border to get it exactly where you think it should be. We could always get exactly the segmentation we wanted in 3-4 minutes, the deviations from the ”correct” segmentation all depends on lack of anatomical knowledge by the operator.

For the test-cases the average time increased to 4 minutes 44 seconds on average, due to feeling greater pressure of really achieving as good segmentation as possible. The minimum time then was 2 min 30 seconds, the maximum 8 minutes.

**Table 2.** Details about the algorithm.

	Parameter	Value
Algorithm	<i>Language:</i>	C++
	<i>Libraries/Packages:</i>	wxWidgets, WISH
	<i>GPU Optimizations:</i>	No
	<i>Multi-Threaded:</i>	No
	<i>User Interaction:</i>	Since the method is interactive, the user can interact with the segmentation process in several ways. A summary is found in Section 3.1, User Interaction.
Machine	<i>CPU Clock Speed:</i>	2.70 GHz
	<i>Machine</i>	HP elitebook 8460p running Windows 7 professional
	<i>Machine Memory:</i>	8 GB
Time	<i>Training Time:</i>	3 hours (for 50 studies)
	<i>Segmentation Time:</i>	3.5 minutes (per study)
	<i>User Interaction Time:</i>	3.5 minutes (per study)

## 5 Concluding Remarks

The method has some parameters, but it is not very sensitive to the values of these. The value of  $\beta$  is quite low ( $0.01 \leq \beta \leq 0.1$ ) since the user rarely adds a single voxel, but a sequence of voxels through a "sweep" by the mouse cursor. Thus, each operation by the brush does not affect the segmentation much, but the total effect by a sequence of voxels is big.

The segmentation of the training set was done in two rounds by a single user; a first round on all volumes and a second round on volumes 00-29 in the training set. The mean Dice's coefficient was 0.82 in the first round and 0.86 in the second round. We believe that this increase is due to the fact that the user gained knowledge about the anatomic structures in the first round resulting in higher accuracy in the second round. The precision also increased; the standard deviation was 0.09 in the first round and 0.05 in the second round. We should also mention that the segmentation of volume 00-29 in the first round resulted in a mean Dice's coefficient of 0.81 with standard deviation 0.11, which also indicates that both the precision and the accuracy improved in round 2.

The average time for segmenting a volume in the training set was 3 minutes and 30 seconds and for the test set 4 minutes and 44 seconds. The increase in time can be explained by the pressure of achieving as good segmentation results as possible for the contest.

The method we have developed is based on a generic approach for interactive image segmentation using a newly developed tool without any built in application specific models. The segmentation results we have obtained are thus to a large extent the result of the knowledge of the user about the anatomy of the prostate. Our experiences from this exercise and from some preliminary work on completely different applications are that Smart Paint is a very effective tool for segmenting objects in 3D volume images even when only 2D display and interaction tools are available. By the results presented in this paper, we can conclude that Smart Paint fulfills requirement 1-3 on an interactive segmentation method [5] stated in Section 1.

## Acknowledgments

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## References

1. Malmberg, F.: Graph-based Methods for Interactive Image Segmentation. PhD thesis, Uppsala University Uppsala University, Centre for Image Analysis, Computerized Image Analysis and Human-Computer Interaction (2011)
2. Malmberg, F., Strand, R., Nyström, I.: Generalized hard constraints for graph segmentation. In: Proceedings of the 17th Scandinavian conference on Image analysis. SCIA'11, Berlin, Heidelberg, Springer-Verlag (2011) 36–47

3. Malmberg, F., Strand, R., Nordenskjöld, R., Kullberg, J.: Seeded segmentation based on object homogeneity. Accepted for publication in Proceedings, International Conference on Pattern Recognition (ICPR 2012), Tsukuba Science City, Japan.
4. Nyström, I., Malmberg, F., Vidholm, E., Bengtsson, E.: Segmentation and visualization of 3D medical images through haptic rendering. In: Proceedings of the 10th International Conference on Pattern Recognition and Information Processing (PRIP 2009), Publishing Center of BSU (2009) 43–48
5. Felzenszwalb, P.F., Huttenlocher, D.P.: Efficient graph-based image segmentation. *International Journal of Computer Vision* **59** (2004) 167–181
6. Mahdavi, S.S., Chng, N., Spadinger, I., Morris, W.J., Salcudean, S.E.: Semi-automatic segmentation for prostate interventions. *Medical Image Analysis* **15**(2) (2011) 226 – 237