From Imprecise User Input to Precise Vessel Segmentations

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Abstract

Vessel segmentation is an important prerequisite for many medical applications. While automatic vessel segmentation is an active field of research, interaction and visualization techniques for semi-automatic solutions have gotten far less attention. Nevertheless, since automatic techniques do not generally achieve perfect results, interaction is necessary. Especially for tasks that require an in-detail inspection or analysis of the shape of vascular structures precise segmentations are essential. However, in many cases these can only be generated by incorporating expert knowledge. In this paper we propose a visual vessel segmentation system that allows the user to interactively generate vessel segmentations. Therefore, we employ multiple linked views which allow to assess different aspects of the segmentation and depict its different quality metrics. Based on these quality metrics, the user is guided, can assess the segmentation quality in detail and modify the segmentation accordingly. One common modification is the editing of branches, for which we propose a semi-automatic sketch-based interaction metaphor. Additionally, the user can also influence the shape of the vessel wall or the centerline through sketching. To assess the value of our system we discuss feedback from medical experts and have performed a thorough evaluation.

1 Introduction

Vessel segmentation is an important preprocessing step in many medical applications, such as surgery planning, research [RHR*] or medical diagnosis [CCA*05]. A crisp 3D visualization of vasculature can only be achieved when using high doses of contrast agent or long scanning procedures, which is often not possible or desirable. While line detection filters [SNS*98] have been used to improve the visualization of vessel structures, they fail to detect deformed vessels which are often the parts most relevant for the user. Therefore, segmentation can still be considered as the gold standard for extracting vasculature prior to visualization as well as for performing a quantitative vessel analysis. The automatic segmentation of vascular structures has been an active field of research for over a decade. However, since a variety of factors make it such a challenging task, no fully automatic solutions exist. Lessage et al. [LABFL09] even state that aiming for a generic, flawless segmentation framework is probably illusory. They argue that a wide variability in shape, possibly caused by aneurysms, stenoses, calcifications or stents, together with the typical challenges in medical image segmentation, i. e., low resolution, noise, artifacts and contrast, make vessel segmentation such a tough problem. Nevertheless, segmentations for these difficult cases are still needed. While there are semi-automatic solutions (see Section 2) that aim to integrate the strengths of interaction and automation, we feel these do not fully utilize the power of visualization, which could make them potentially more intuitive and thus usable. Furthermore, some of these systems approximate the cross section using circles or ellipsoids (therefore not giving full control to the user) or require specialized hardware (see Section 2). In this paper we propose a visual vessel segmentation system that allows the user to edit a vessel's centerline and its surface in several linked views. These interactions are part of a two step workflow, where the user first focusses on the centerline, which is the basis for the subsequent segmentation. After an initial centerline has been defined through sketching, it can be corrected and its quality can be assessed before an initial segmentation is computed. At the same time, the system has been designed to be able to generate surface segmentations of high precision, which is required in many application cases, such as for instance vessel quantification as well as blood flow simulation based on real-world data [CCA*05]. In our system, the user is also able to correct the surface segmentation by sketching. To limit user interaction and therefore promote efficiency we employ uncertainty visualization as a tool to convey the reliability of the intermediate results to the user and intuitively guide the input to introduce certainty in the system.

To the best of our knowledge this is the first semi-automatic vessel segmentation tool that gives the user full control over centerline and vessel surface. We propose new methods for visualization, interaction and segmentation to facilitate high efficiency and precision:

- To maximize relevant information for the user in one view without requiring further configuration of the rendering, we developed a new type of Curved Planar Reformation (CPR), the Importance Driven CPR.
- To add new centerline segments, we propose a novel sketch based interaction technique, which resolves ambiguities and inaccuracies in the user input.
- We propose a seed volume generation technique to reduce

computation and user interaction time required to perform the actual vessel segmentation.

2   Related Work

Since the literature on vessel segmentation is too extensive to discuss in its entirety we are focussing on interactive techniques and discuss the main classes of algorithms to motivate the choices we made while designing our system. We refer the reader to the survey by Kirbas and Quek [KQ04] for an overview of additionally existing techniques. Olabarriaga and Smeulders point out in their survey on interaction in medical image segmentation, that fully automatic methods sometimes fail and require intervention by the user [OS01]. They also emphasize that interaction is usually only marginally discussed in segmentations papers, which is a tendency still valid today. However, there are exceptions which are the most relevant techniques for our approach. Direct drag-and-drop modifications of the segmentation have been proposed by Timinger et al. [TPvB*03], which have also been incorporated into our system. Kang et al. [KEK04] discuss editing tools for medical image segmentation in general. Their approach allows to modify segmentation masks, but does not allow an iterative processing such that the modifications are fed back to the segmentation algorithm. We therefore consider this approach a postprocessing of the segmentation instead of a true integration of interaction. Serra et al. [SHCP97] discuss a system in which the user can specify the centerline by manually tracing it with a 3D input device. The extent of the vessel can then be modelled as a tube by manually adjusting the diameter for each node of the centerline. Owada et al. present several approaches for sketch-based interactive segmentation [ONI08]. Similar to our vessel sketching approach, their techniques make use of the *sweep surface*, an extension of the user sketch into the screen. From the sketched line two adjacent strokes are automatically generated, which are used to compute the segmentation of the desired structures. However, their axis-tracing tool requires a clear view of the structure to segment and follows an indirect approach to fit into the Volume Catcher pipeline [ONI05]. Abeysinghe and Ju discuss a tool to interactively determine skeletons of intensity volumes by clicking and painting on a 3D isosurface rendering [AJ09]. The proposed technique therefore first precomputes a skeleton of an intensity volume and then uses the user input to correct topology errors. However, the resulting skeletons shown in the paper do not look smooth and an isosurface rendering could be problematic for data sets with a low signal to noise ratio. Kohlmann et al. propose a contextual picking approach based on ray profiles which is able to select structures after the user has clicked on a 3D rendering [KBKG09]. The authors also propose interactive calculation of centerlines as application case, but the resulting line is not centered in the vessel and spatial coherency along the sketched line is not exploited. Jeong et al. present a system called NeuroTrace, which allows the segmentation and visualization of neural processes in large data
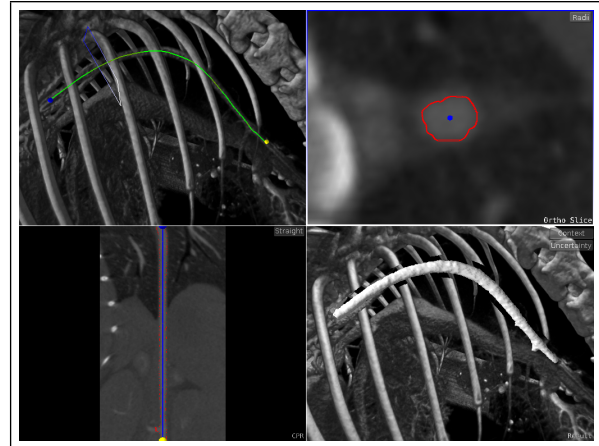

Figure 1: *System Overview: Main 3D view (upper left), orthogonal slice view (upper right), CPR (lower left), 3D result view (lower right).*

sets [JBH*]. To make the system scalable the segmentation result is approximated by a set of elliptical cross sections. It should be further noted that branching is not supported by this technique. Helmstaedter et al. [HBD11] propose a system for neurite reconstruction that relies on the skeleton of a neurite to compare and merge reconstructions by different users. Wang and Smedby discuss integration of automatic and interactive methods for coronary artery segmentation [WS10]. Their system allows specification of additional seeds for the virtual contrast injection algorithm and modification of centerline end points. For analysis purposes the vessel is segmented using a level set approach in 2D in a CPR and a cross-sectional view. This segmentation can also be post-processed by the user with a tool called *repulsor*. Aside from the discussed shortcomings we feel that the mentioned systems only utilize visualization as far as necessary but do not explore how visualization can be exploited to actually improve segmentation results.

La Cruz evaluates the accuracy of centerline calculation techniques on cross-sectional slices [Cru03]. Based on her findings we chose a raycasting based approach utilizing user specified thresholds.

3   Design Considerations

We have decided to come up with a semi-automatic, visually guided approach as a solution to the vessel segmentation problem. The goal was to exploit intuitive interaction metaphors in order to generate new or improve existing vessel segmentations, and thus combine the strengths of humans and computers. This has been achieved by building a segmentation system that allows the user to intuitively and efficiently segment vessels. Although the system is built up on top of automatic segmentation algorithms, we are still able to provide full flexibility to the user.

Since a vessel's centerline is often used in the vessel segmentation process [LABFL09], we have also decided to center

our system around this compact vessel representation. Additionally, centerlines are commonly used in vessel analysis software and for visualization purposes [PO08]. In order to generate a centerline from segmentation results a skeletonization algorithm has to be applied. Besides introducing additional computations, these algorithms can introduce other problems [BFLC02].Furthermore, user modifications would be lost after recomputation of the centerline, e. g., when the segmentation has been modified through user input. As we will discuss in this paper and also postulated by Lesage et al. [LABFL09], the reverse case is less problematic, such that the centerline can be used as a starting point for an efficient and accurate segmentation. When segmenting the surface of a vessel, the user should have the ability to modify the result in an efficient and intuitive manner, without having to navigate through each slice intersecting the vessel. Furthermore, since we aim at high precision, we did not want to explicitly enforce smoothness constraints on the surface segmentation. The random walker algorithm [Gra06] is widely used for image segmentation since it nicely complies with these criteria. It is a probabilistic segmentation algorithm that has been successfully utilized before in an interactive segmentation system by Praßni et al. [PRH10]. Top et al. [THA11] propose a very similar system. However, Praßni et al. point out that no thin structures, potentially intersecting multiple slices, could be segmented with their approach, since that would require the user to set an unmanageable number of seed points along the whole extent of the target structure. Because this would hamper the application of the random walker approach for vessel segmentation in general, we have overcome this limitation by exploiting a semi-automatic seed placement strategy. This has not only the benefit that it reduces user input but also minimizes the computation time itself.

While the concepts introduced above allow the user to influence a segmentation by first defining the center line and then modifying the segmentation result itself, they do not provide any clues in which areas interaction is required. Only by providing appropriate visual feedback, the user will be able to judge the current segmentation result and thus be able to assess the accuracy of the segmentation to be generated.

By definition, a centerline should run through the center of a vessel having potentially a circular cross section. However, in abnormal cases where the vessel shape is deformed, the situation might be less clear and further inspection by an expert user may be required. Therefore, we use the shape of the vessel cross section for each point along the centerline as an indicator for the centerline reliability. We define the centerline uncertainty $cl_u = 1 - \frac{r_{min}}{r_{max}}$ to be 0 for circular shapes and to increase with irregularity. In order to convey this information intuitively, we exploit a green (=certain) to red (=uncertain) color mapping.To depict the uncertainty of the segmentation itself, we exploit the probability field of the random walker algorithm, and display uncertain regions also in red. Thus, we are able to guide the user during the process when generating a precise segmentation.

Because an intuitive use of the system was one of the most important design goals, we decided to base the user input mostly on sketch-based interaction metaphors. Therefore, it becomes possible for the user to quickly sketch the vessel tree on a 3D rendering in order to extract an initial centerline. In our expert evaluation we were able to show that this is beneficial when compared to alternative techniques (see Section 6). As discussed in Section 2, sketching has been used before in the context of vessel segmentation. However, our approach is different in the sense that we directly transform the drawn strokes into a centerline. Furthermore, we support a semi-automatic linking of adjacent centerlines. When modifying the segmentation itself later on in our workflow, sketching can also be used, as it is a commonly used technique in segmentation tools. By initiating the surface segmentation technique based on these seeds and sketched centerlines, we inherently achieve a coherent segmentation modification, since the algorithm propagates the seeds in three dimensions. Furthermore, it allows persistent segmentation editing, since the user modifications are further valid after changing the centerline or seeds and rerunning the segmentation process which is not the case for all interaction techniques for segmentation manipulation [KEK04].

We have selected four views (see Section 4) with the goal to provide all information which is necessary to perform a vessel segmentation efficiently and effectively. The data structures used for representing the segmentation results is also something we have considered during the design of our system. Since we want to achieve a precise segmentation, approximation approaches such as truncated cones, fitted ellipses [JBH*] or convolution surface are not appropriate. Instead we have decided to directly store and visualize a segmentation volume.

3.1 Workflow

The first step in the workflow (see Figure 2) is the optional usage of an automatic vessel segmentation algorithm, which resulting centerline could be used as a starting point for our system. Additionally, the user has to provide an intensity window for vessels, which is done interactively in a slice view of the volume. This intensity window can be rather broad, as it is only used to throw away voxels clearly belonging to the background. We found that this window only needs little adjustment when using the same scanning protocol. The users can now use the sketching functionality to insert own centerline segments. To further modify the centerline, points of the centerline can be dragged in 3D. Alternatively this dragging functionality is also possible in the orthogonal slice view as well as the CPR. The induced movement is smoothly propagated to the neighbors in all views. Pruning of erroneously detected segments can also be performed easily in these views. When the user adds additional centerlines, newly sketched segments are automatically connected to the existing tree by considering their distance to the existing centerline segments.

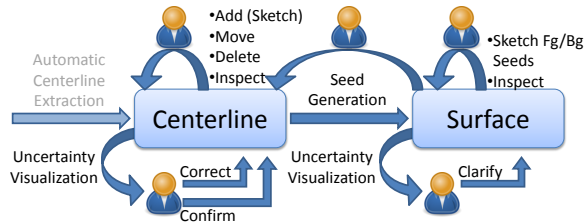After the user is satisfied with the centerline skeleton, which

Figure 2: *Workflow: The user can modify centerline and vessel surface. Editing of both aspects of the vessel segmentation is sketch-based and driven by uncertainty visualization. The centerline determines which parts of the vasculature are to be segmented. Because modification of the surface is not done in a post-processing step but by sketching seeds, the user can keep editing the centerline without losing any work done on the surface.*

also marks the part of the volume to be segmented, the surface segmentation can be started. The user can then inspect the result and modify it by placing additional seeds in one of the 2D views. To guide this seed placement, segmentation parts with a high degree of uncertainty are highlighted.

4 Visualization Techniques

Main 3D View The main 3D view (see Figure 1 (upper left)) shows a direct volume rendering of the data set, since standard 2D views are not sufficient in many cases, i.e., when vessels cannot be cut with a single slice. In addition to the centerline of the segmentation, it contains cues to support mental linking of the views. The centerline geometry is considered as the main communication and interaction element in the main 3D view, and is thus overlayed over the vessel. While this results in a false depth ordering, we found it to be visually more expressive using a geometry integration approach as the one presented by Scharsach [Sch05]. We have tested this technique and found it to result in a rather occluded geometry, which hampered the perception of the uncertainty encoding. Therefore we decided to render the geometry over the volume, ensuring compatibility with all data sets, and lessening the requirements on the transfer function while clearly displaying all color cues. As further discussed in Section 5, we consider centerline positions of irregular cross sections as potentially uncertain and color them red. A user certainty value based on the distance to the next user confirmed or corrected point along the centerline is added to the this shape uncertainty.

Orthogonal Slice View While the 3D view provides a good overview of the vessel, it does not allow the inspection of the vessels interior. Therefore, a cross section view is crucial. It further allows an in-detail inspection of the shape at a certain centerline point, and provides an important basis for the interaction techniques allowing to modify the centerline as well as the segmentation results (see Section 5).

After the segmentation has been calculated, we derive and visualize the uncertainty by using a simplified version of the approach proposed by Praßni et al. [PRH10] to guide the

user interaction. Similarly to their approach, we exploit isolines for the depiction, but we limit the display of these lines to two, because the area of uncertainty turned out to be quite small in practice. We believe that this rather small uncertainty region is due to the large number of seeds that we generate automatically.

CPR The curved planar reformation [KFW*] is another well established visualization technique that allows to inspect a vessels interior, and has therefore been also integrated into our system. Another important purpose of the CPR views is the navigation through the orthogonal slices.

Importance Driven CPR The implemented classic CPR types rely on a static vector of interest, which may not necessarily show the parts of the vessel needing further attention. While the vector of interest can be rotated to point in a direction that allows the user to inspect and correct problematic parts, this requires user interaction and there may be multiple directions of interest. There are variants of the CPR that display more than one slice of a vessel, like helical CPR [KWFG] or thick-CPR [KFW*]. However, we wanted the user to immediately see problematic sections and be able to react in the form of centerline dragging or sketching of additional seed points, which would not be possible with these types because one pixel on the screen cannot be clearly associated with one point in the dataset. We therefore propose a new type of CPR where the vector of interest is dynamically guided by importance. Importance is determined by the medialness of the centerline as well as the uncertainty of the surface segmentation. For each point on the centerline we cast rays in multiple directions in the cross-sectional plane (we found that 150 rays gave good results), these are possible vectors of interest. We stop at the point where the probabilistic segmentation is 0.5 and set the surface uncertainty s_{uc} as the distance to the next certain voxel (see the next Section). The centerline uncertainty for each ray is defined as described in Section 3. We then define the cost for each ray as $c_{ray} = max(cl_{uc}, s_{uc})$ and compute a smooth sequence of vectors of interest that maximizes the overall importance to the user and generate the CPR from these vectors instead of a static one (see Figure 3). The user can therefore immediately spot problems with both elements of the vessel segmentation without having to configure the vector of interest. Furthermore, a more efficient surface for providing correction through strokes is provided since the importance driven CPR will rotate to display lengthy uncertain parts (e.g., other vessels running along the vessel to be segmented). After the uncertainty is removed the CPR will be re-evaluated to display the next most important parts.

3D Result View Inspired by the approach presented by Viola et al. [VKG] and Straka et al. [SCLC*], we use a cutaway technique to show context while preserving an unobstructed view on the segmentation result. The main purpose of this view besides inspecting the shape of the resulting segmentation is to visualize the uncertainty information derived from the probabilistic segmentation. By masking the certain voxels (i.e., [0.05, 0.95]) from the probability volume and apply-
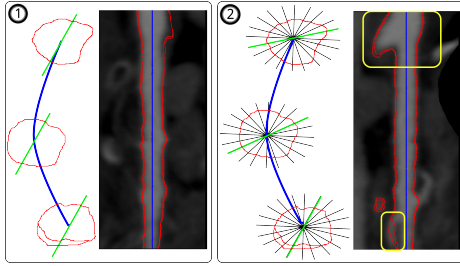
Figure 3: *Importance Driven CPR: We maximize relevant information in the CPR rendering by making the vector of interest (green) importance driven. The vector of interest is static for a straightended CPR view (1). Based on the shape of the vessel (red) and the certainty of segmentation we dynamically rotate the vector of interest (2). This results in immediate visibility of possibly problematic centerline positions as well as surface segmentation uncertainties (yellow).*
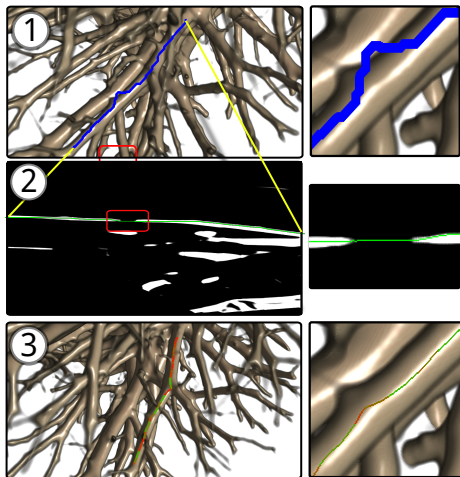

Figure 4: *Adding new segments: 1) The user has sketched a part of the vessel tree to be segmented. The sketch does not have to be centered or even on the vessel all the time (see inlet) 2) The sketch is projected into the screen and the path with minimal cost is determined on the resulting image. Note how the gap introduced through the inaccuracy in the sketch is handled. 3) The line is centered inside the vessel using an active contour approach. This step also draws all points outside the vessel inside (see inlet).*

ing a distance transform we generate an uncertainty volume. A high distance to regions of certainty is therefore considered uncertain (see Figure 7).

5   Interaction Metaphors

Centerline Interaction In order to add new centerline segments, the user draws a stroke on top of the vessel to be segmented in the main 3D view. To transform a user sketch into a centerline, we need to compute the correct depth value for the line drawn by the user (see Figure 4 (1)). In order to exploit the spatial coherency we use a technique related to

the one proposed by Owada et al. [ONI05]. We generate an image from the line extruded into the view direction by reading entry and exit point for each point of the line. We can therefore also correctly handle clipping planes used in the 3D view. The intensities are based on the user provided vessel windowing (see Section 3.1). To find the correct depth we calculate the path with the lowest cost using dynamic programming (see Figure 4 (2)). As can be seen in Figure 4 (1) and the accompanying video, the stroke does not have to be precise, the minimal path algorithm corrects even deviations from the vessel (see Figure 4 (2)). To further increase the certainty that the computed centerline matches the user's intent, we incorporate the visibility based on the used transfer function. This is done by accumulating the alpha value in extrusion direction and modulating the cost with this visibility factor. Ambiguities where there is a second structure at the same position on the screen at a different depth are therefore resolved. Since vascular structures are usually a connected system we search for segments close to the ends of the depth-corrected line and attach them to the centerline-tree. To correct for imprecise user input and estimation of intended depth we center the line in the vessel using an active contour technique. In order to pull the line towards the center of the vessel we further use an external force that calculates the center for the current position and tangent using circular raycasting [Cru03] and pulls the point in this direction. The magnitude of this force is modulated by the centerline uncertainty cl_{uc}. For circular profiles the force is the strongest, while it is lower for irregular shapes. This external force is ignored for points that are outside the vessel, i. e., the intensity at this point is outside the user specified vessel window. Therefore, parts of the line where the user has not hit the vessel are pulled inside the vessel (see Figure 4 (3)).

User Correction As we have just discussed we consider the position of the centerline where the circular raycasting results in circular shapes as certain. If the shape is irregular the user should confirm the position of the centerline or correct it in one of the views (see Figure 5).

Segmentation Modification The surface segmentation algorithm needs seed points to be set in order to segment the vessel structures. To place these seed points, we generate foreground and background seed volumes based on conservative estimates of the inner and outer radius of the vessel. A voxel is considered as background voxel if it is not within the outer radius of any centerline segment. If a voxel is inside the inner radius of a centerline segment the voxel is marked as foreground voxel. Only the remaining voxels, usually a small fraction of the volume, need to be segmented by the random walker algorithm. This process is shown in Figure 6. From the user confirmed centerline we cast circular rays for each point. The inner radius is the minimum distance a ray can be cast while being strictly inside the threshold. The outer radius is the minimum distance a ray has to travel to be safely outside the intensity window. We use a safety margin on both calculations to account for a limited number of rays.
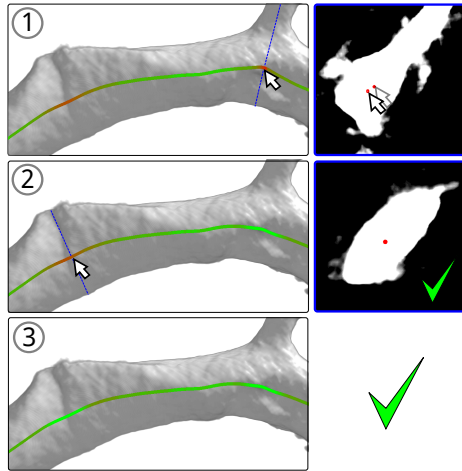
Figure 5: *Centerline Uncertainty: Guided by red highlights on the centerline the user inspects parts of the centerline where the position is considered uncertain. 1) The user moves the mouse to the red section of the centerline to find it displaced due to the branch. By dragging the centerline on the orthogonal slice the position is corrected. This section of the centerline is therefore marked as user-corrected. 2) The user inspects another section of the centerline marked as uncertain, but is satisfied with the current position. By pressing a hotkey the position is accepted and marked as user-confirmed. 3) The centerline is now completely green, which means that it is either user-corrected, user-confirmed or has a regular shape and is therefore considered certain.*

This approach can degenerate in two ways: The inner radius could become zero and only the centerline itself would get rasterized into the foreground seed volume at this position. This is similar to the approach proposed by van Bemmel et al. [vBVN04] who initialize a level set segmentation on the centerline. Alternatively, the outer radius can become large for noisy or low contrast data sets, which may happen especially at branches. However, this only increases computational cost and does not lead to an unstable processing. Based on the calculated radii we now build the foreground and background seed volume (see Figure 6 (2)), and the random walker algorithm segments the layer between both. The resulting segmentation is displayed in Figure 6 (3). Because of the large number of seeds, the amount of unseeded voxels is comparatively low and we can handle larger data sets (up to 440x300x1100) and keep times of user-inactivity lower then when using only a small number of hand drawn seeds. Guided by the highlighted areas shown on the segmentation, the user can move the mouse on these sections to inspect it in the linked views (see Figure 7).

6 Evaluation

In their survey on interaction in medical image segmentation Olabarriaga and Smeulders [OS01] list accuracy, repeatability and efficiency as the main criteria, which influ-
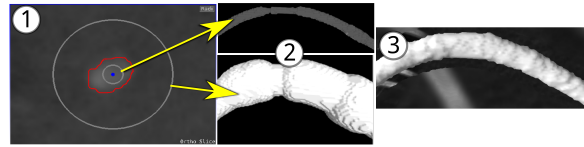

Figure 6: *Seed Volume Generation: 1) Based on the centerline the algorithm calculates conservative estimates of the inner and outer radius (gray circles in slice view). 2) From these estimates seed volume for foreground (upper) and background (lower, inverted) are generated. 3) The resulting segmentation, which is also visible as red line between the inner and outer circle in the slice view.*
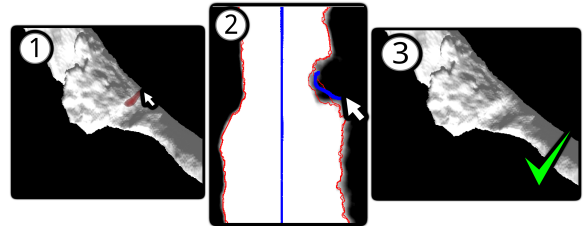

Figure 7: *Surface Segmentation Uncertainty: 1) Regions where the segmentation of the surface is uncertain are highlighted in red. When hovering the mouse over the surface the orthogonal slice view and CPR are linked accordingly. 2) The user corrects the uncertainty by sketching additional seeds in the CPR. 3) The uncertainty is fixed.*

ence the quality as well as the usability of a segmentation system. **Accuracy** can be more directly exploited as a quality criteria when dealing with automatic segmentation techniques. When using interactive approaches an expert user can modify the result until it best reflects his or her expert knowledge, which is called *potentially accuracy* [OS01]. In our system, this can be done by sketching additional seed points, which given in a dense layout directly define borders. To investigate the degree of accuracy that can be achieved when using our system we evaluated the outcome of our system using the carotid bifurcation algorithm evaluation framework [HZF*11]. This framework is a good fit to evaluate our system because it focusses on a small part of the vasculature and provides a standardized evaluation system, comparing the submitted segmentation to averaged ground truth, provided by three experts. The dataset consists of 56 computed tomography angiography (CTA) images (acquired on different scanners) of the carotid arteries, some with stenosis. We did not utilize the starting points provided with the datasets to perform our segmentation but instead sketched the centerline. We segmented all datasets and our results were compared to the ground-truth using three metrics: Dice similarity measure, mean surface distance (MSD) and maximum surface distance. Table 1 shows minimum, maximum, and average values for each metric. The average Dice measure was 90.0% — in only three cases the Dice similarity measure between our results and ground-truth was less than 85.0%. Table 2 shows the average grades

of our system and of the three experts. Our average results are within a few percent of the inter-observer variability, which we achieved with one dataset. We attribute this difference mostly to the approach used to generate the ground truth data: a manual, probably very time consuming process in which the cross-sectional contours were modeled using splines. Resulting segmentations are therefore smoother than the output of our system, which is more closely coupled to the data. This is most notable at secondary branches which were not to be included in the segmentation and account for the relatively large maximum surface distance. We argue that a more circular cross-section at these branching points is not more true to reality than the protrusion which remains when removing the branch with a few sketched background seeds and therefore did not spend too much time modeling these sections to match the ground truth. Overall, we conclude that our technique enables users with no medical training to create precise vessel segmentations.

Repeatability is mainly influenced by difference in user input or judgment which may lead to a high variability of the results [OS01]. To test for the influence of differences in sketching, we used a ground truth segmentation of a vessel segment in a contrast enhanced CT scan, and asked three users to perform a segmentation with our system. We instructed the three novice users having no medical background in the use of our system, and explained the task to be performed. The result was compared to the ground truth segmentation using the dice metric. The obtained dice scores (93.7%, 94.4%, 94.2%) confirm a good repeatability of segmentations results.

Efficiency of semi-automatic systems can be estimated by considering two key components: usability of the interactive parts and performance of the automatic parts.

When judging the amount of user input one should keep in mind that it is not the aim to construct large vessel trees manually but to successively add or correct a reasonable amount of specific vessels. Similar as other authors working on sketching techniques, we believe that the sketching directly communicates that no precise interaction is required. We argue that sketching vessels on a 3D rendering is as intuitive and predictable as possible, which our domain experts confirmed. The placement of additional seeds for the surface segmentation and movement of the centerline is only necessary where the automatic approach failed and has not to be done on a slice basis. Regarding the performance of the automatic parts, we have implemented the surface segmentation and sketch-extrusion on the GPU to facilitate a smooth interaction.

Expert Evaluation To evaluate the practical value of our approach we have organized an interactive hands-on session of our system with our medical partners. The group consisted of four researchers interested in the vascular system and working with scans from different modalities on a daily basis. One possible application case of our system is the quick segmentation of parts of the vasculature in which

Table 1: *Summary lumen (generated using [HZF*11])*

Measure	% / mm			rank		
	min.	**max.**	**avg.**	**min.**	**max.**	**avg.**
L_dice	81.3%	95.5%	90.0%	3	4	3.98
L_msd	0.21mm	1.31mm	0.54mm	4	4	4.00
L_max	0.78mm	8.04mm	5.96mm	3	4	3.98
Total (lumen)				**3**	**4**	**3.98**

Table 2: *Averages lumen (generated using [HZF*11])*

Team name	Total success	dice		msd		max		Total rank
		%	**rank**	**mm**	**rank**	**mm**	**rank**	
Our technique	41	90.0	4.0	0.54	4.0	5.96	4.0	4.0
ObserverA	41	95.1	1.6	0.10	1.7	0.54	1.8	1.7
ObserverB	41	94.6	2.2	0.11	2.2	0.62	1.8	2.1
ObserverC	41	94.4	2.2	0.12	2.1	0.72	2.4	2.3

the user is interested. The need for this type of segmentation was confirmed for research as well as clinical use. Due to the intuitive and quick sketching of vessels the approach was seen as a viable alternative to selection of parts of a full segmentation. A significant part of the scans our partners use are small animal CT scans, which make vessel segmentation even more challenging due to the small size of the species under observation. In addition, abnormalities of the shape of vessels are common in these scans. Therefore automatic approaches which rely on strong contrast or shape based approaches fail and manual segmentation needs to be performed. They appreciated the segmentation directly on the basis of a 3D rendering, especially for cases where one vessel cannot be cut by a single slice. Exact, user controlled placement of the vessel wall as well as the centerline was also confirmed as important criteria for a vessel segmentation system by our medical partners. Considering parts of the vessel with irregular shape as uncertain was perceived as a sensible approach. The red-green color scheme was intuitively understood and our technique of user confirmed and modified points used to guide the user towards confidence about the segmentation was appreciated. We also discussed the visualization techniques used in our system and the applicability of all views was confirmed. However, the direction of the CPR was unclear and the inclusion of start/end markers in the 3D view was suggested.

7 Conclusion

In this paper, we discussed the design, implementation and evaluation of an interactive, visually guided vessel segmentation system. The system has been designed for two usage scenarios: the correction of the results of automatic segmentation algorithms and the fast, user guided segmentation of parts of the vasculature that the user wants to inspect or analyze. To provide intuitive solutions for these scenarios, we have exploited a semi-automatic approach. On the interaction side, the key concept of the system is a sketch-based user interface, which allows to generate precise vessel segmentations from rough strokes quickly drawn on a 3D view. While the actual segmentation is performed using the random walker algorithm, it can be also modified through the

proposed sketch-based interface. In combination with these interaction techniques, we exploit visualization techniques arranged in linked views, which help the user to assess the quality of the current segmentation and thus support its modification. In this context, a key concept is the uncertainty visualization, which conveys the reliability of the intermediate results in a concise way. We have thoroughly evaluated our system using the carotid bifurcation lumen segmentation framework and discussed opinions by a group of expert users from the medical domain. Their feedback has shown that there is a high demand for such a system in the medical/biological community.

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