

# Segmentation of the Vascular Tree in CT Data using Implicit Active Contours

Karsten Rink, Arne-Michael Törsel and Klaus Tönnies

Institute for Simulation and Graphics, University of Magdeburg, 39016 Magdeburg

**Abstract.** We propose an algorithm for the segmentation of blood vessels in the kind of CT-data typical for diagnostics in a clinical environment. Due to poor quality and variance in the properties of the data sets a two level approach using implicit active contours is chosen for the task. A fast pre-segmentation using the fast marching method followed by propagation of a sparse field level set allows a robust segmentation of the vascular tree. Evaluation of the results and observed problems are described.

## 1 Introduction

The detection and segmentation of blood vessels are important parts of many medical applications. The segmentation results can be used to analyse the vessels themselves, e.g. to find aneurysms, stenoses or malformations. Furthermore, knowledge of the location and size of the blood vessels is essential for operation planning. One possible application is neck dissection: The local lymph nodes are the first stage of a lymphogenous metastasis of a tumour. Since the involved lymph nodes may in turn may invade neighbouring structures, they should be removed. This requires finding the boundaries between blood vessels and the enlarged lymph nodes in order to decide if an operation is possible.

## 2 Related Work

A large number of methods has been applied to blood vessel segmentation[1]. Examples are multi scale approaches, centerline detection[2] or region growing[3].

Most vessel segmentation methods are tested with angiography data (XRA or MRA) or contrast-enhanced MRI. Boundaries of the vessels are usually clearly visible in these modalities and purely data driven approaches, e.g. the aforementioned region growing methods, give good results.

Another approach for segmentation is the use of active contours. The advantage of these models is the combination of features derived from the data and assumptions about properties of the chosen object. Besides the well-known explicit models (i.e. snakes, etc.) this group also includes implicit models like level set methods[4][5] and fast marching methods[6].

Implicit contours are globally defined which allows a combination of data- and model-driven strategies. This seems promising since the location and size

of blood vessels are different for every patient, making an explicit formulation for a model difficult. A pure data-driven approach on the other hand will be unreliable if boundaries the vessels cannot be easily identified.

Level set methods have already been applied to blood vessel segmentation (see for instance [7]) but due to the artifacts and partial volume effects in our data the task is challenging.

### 3 Blood vessel segmentation using level set methods

We use a two level approach for the segmentation of the blood vessels in our data: After preprocessing the data with rank order filters we first perform a pre-segmentation using the fast marching method. This algorithm converges very fast and allows for the user to just choose a few seed points for initialisation.

To get the final result we start a sparse field level set algorithm[8] initialised with the contour from the fast marching result.

The propagation of the front is stopped in both stages of the segmentation process if the grey values of pixels on the front deviate too far from expected grey values for blood vessels in the given data set or if the front meets a boundary. During the level set stage we also use a regularisation term based on local 3D curvature.

The level set equation

$$\Phi_t + F|\nabla\Phi| = 0 \quad (1)$$

has a speed function  $F$  defined as

$$F = F_I * (F_A + \alpha * F_K) \quad (2)$$

where for each pixel  $(x, y, z)$  in the data set  $F_A$  is the advection speed,  $F_K$  is the local curvature and  $F_I = F_I(x, y, z)$  is the image-based speed term defined as

$$F_I(x, y, z) = (1 + \beta * (\nabla I(x, y, z))^2 + \gamma * (I(x, y, z) - I_{vessel}))^{-1}. \quad (3)$$

The weights  $\alpha$ ,  $\beta$  and  $\gamma$  enable a propagation specific to the features of a given data set; a high value meaning that this feature has a large influence and vice versa. Finally, the term  $I_{vessel}$  denotes the grey values interval associated with blood vessels.

As noted in [4] it is possible to incorporate an exponential function for the image term instead of the reciprocal one we use to achieve a faster convergence. However, experiments with our algorithm showed that this leads to a loss of robustness.

**Table 1.** Examples for the resolution of the data sets.

Data set	Pixel spacing	Slice spacing	Slice thickness	Contrast agent
01	0.28	3.0	3.0	yes
03	0.33	3.0	3.0	no
09	0.45	3.0	3.0	no
15	0.47	2.1	1.0	yes
19	0.53	5.0	5.0	no
22	0.43	3.0	2.0	no
23	0.58	6.0	5.0	yes
25	0.41	1.5	3.0	no

## 4 Results and discussion

We tested our algorithm for segmentation of blood vessels on 10 CT-data sets representative for diagnostics in a typical clinical environment. The resolution and quality vary substantially between the different data sets (see table 1). The data is often corrupted by noise, by inhomogeneities and by metal artifacts from dental inlays. Depending on slice thickness partial volume effects may further complicate analysis of the data. With half of the data sets a contrast agent was used.

Using our method we were able to segment most of the vessels contained in data with only a single seed point at the first slice of the data set. More seed points in other slices may result in a more exact segmentation and a faster convergence of the propagation process.

During the first level of our segmentation process we used an extremely cautious propagation strategy to avoid leaking of the contour. In most of the cases we were successfully able to avoid this. The front leaked out of the blood vessels in cases of extreme metal artifacts due to dental inlays (figure 1(a)) and when a contrast enhanced vessel was located directly beside a bone (figure 1(b)). A different method for pre-segmentation is necessary in these cases since there is no way (even for a human) to locate the boundary of the vessel.

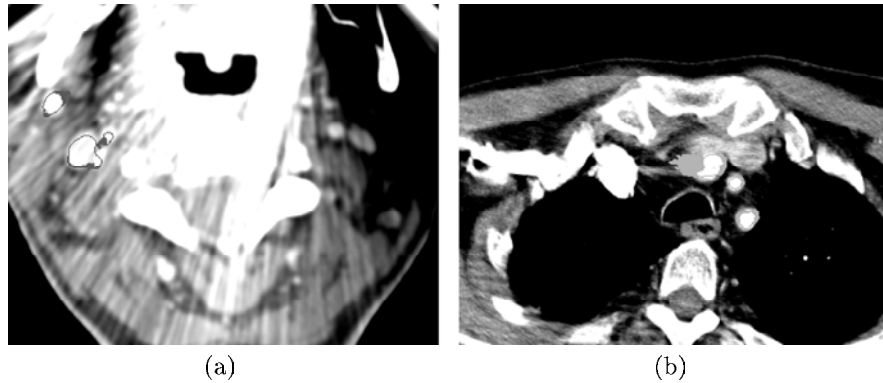
Results of our algorithm were evaluated by two experts with medical background to ensure the correctness of our segmentation.

Blood vessels with a large diameter (arteria carotis externa, -interna, etc.) were always segmented correctly. Depending on the quality of the data an undersegmentation of up to 10% of the diameter of the vessel has been observed. This apparent undersegmentation proved often to be the correctly segmented lumen. Pixels not segmented were classified during evaluation as connective tissue.

Due to the large slice spacing and -thickness of the data sets the algorithm could not follow smaller vessels branching off at a steep angle if either the lumen of the vessel had a large disparity to the lumen in the following slice or the vessels merged with the background due to partial volume effects. In both cases it is not possible to follow the vessels without further modification on our algorithm.

Except in the cases mentioned vessels with a diameter as low as 5 pixels were segmented correctly. Especially in data sets where a contrast agent was used, the

**Fig. 1.** (a) The image shows metal artifacts originating from dental inlays. The vessels on the left side are segmented correctly due to regulation constraints of the model. Boundaries for the vessels on the right side are not recognisable. (b) On the left side a contrast enhanced vessel seemingly merges with the bone. The vessels on the right side are correctly segmented but one vessel is lost due to partial volume effects.



contrast increases in cranial direction, allowing a more accurate segmentation (see figure 2(a)).

Vessels with an even smaller diameter were often not clearly distinguishable even by the experts evaluating our results. This can be attributed to partial volume effects and noise.

All of the mentioned results were obtained using an identical parametrisation for all data sets. With a special parametrisation for each data set results were usually more exact but the experts evaluating our results stated that the results with the identical parametrisation were adequate.

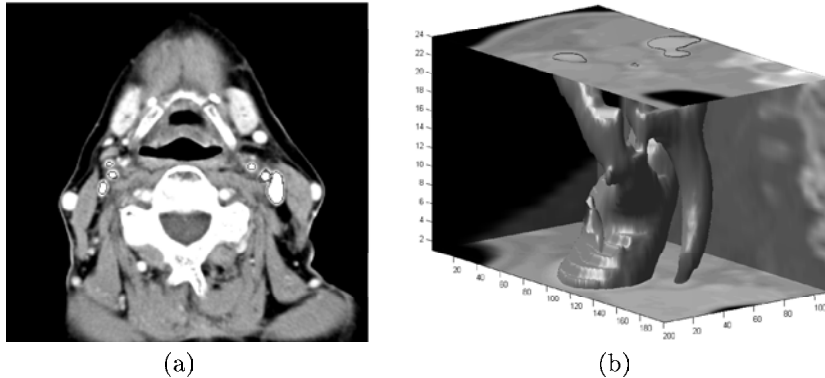
The time needed for convergence of the front propagation process differed extremely based on the number of slices of the data set, the quality of the data and the quality of the intermediate result of the fast marching method. Computation times ranged from less than a minute to about 20 minutes in cases where large parts of the final result had to be covered by the level set algorithm itself.

## 5 Conclusions and future work

We presented an algorithm for the segmentation of the vascular tree in CT-data of the human head and neck section using a modified level set algorithm. Results of our segmentation proved to be adequate for vessels with a diameter of at least 5 pixels (1.5–2.5 mm).

For the neck dissection application mentioned in the beginning only sub-mandibular vessels are of interest. These vessels still have a large diameter and results of the front propagation are adequate.

**Fig. 2.** (a) Segmentation of vessels with a small diameter. (b) 3D visualisation of a front propagation result.



Segmentation results would certainly be improved if a reliable algorithm for detection of seed points throughout the data set could be incorporated. Parameter adaption for different parts of the data set would also improve the accuracy of the final result.

**Acknowledgements.** We like to thank the university hospital in Leipzig for providing the data sets. We are also grateful to Karin Engel and Andreas Fügner for the discussion and their help with the evaluation of the results.

## References

1. Kirbas C, Quek F. A Review of Vessel Extraction Techniques and Algorithms. *ACM Computing Surveys* 2004;36(2):81–121.
2. Wesarg S, Firlle EA. Segmentation of Vessels: The Corkscrew Algorithm. In: *Proceedings of the SPIE Conference on Medical Imaging*, vol. 5370; 2004. .
3. Boskamp T, et al. A New Vessel Analysis Tool for Morphometric Quantification and Visualization of Vessels in CT and MRI Datasets. *Radiographics* 2004;24:287–297.
4. Malladi R, Sethian JA, Vemuri B. Shape Modelling with Front Propagation: A Level Set Approach. *IEEE Trans on PAMI* 1995;17(2):158–175.
5. Sethian JA. *Level Set Methods and Fast Marching Methods*. Cambridge University Press; 1999.
6. Sethian JA. A Fast Marching Level Set Method for Monotonically Advancing Fronts. *Proc Nat Acad Sci* 1996;93(4):1591–1595.
7. van Bemmelen CM, et al. A Level-Set-Based Artery-Vein Separation in Blood-Pool Agent CR-MR Angiograms. *IEEE Trans Med Imaging* 2003;22(10):1224–1234.
8. Whitaker RT. *Isosurfaces and Level-Set Surface Models*. School of Computing, University of Utah; 2002.