Model-based Segmentation of Pathological Lymph Nodes in CT Data

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ABSTRACT

For the computer-aided diagnosis of tumor diseases knowledge about the position, size and type of the lymph nodes is needed to compute the tumor classification (TNM). For the computer-aided planning of subsequent surgeries like the Neck Dissection spatial information about the lymph nodes is also important. Thus, an efficient and exact segmentation method for lymph nodes in CT data is necessary, especially pathological altered lymph nodes play an important role here.

Based on prior work, in this paper we present a noticeably enhanced model-based segmentation method for lymph nodes in CT data, which now can be used also for enlarged and mostly well separated necrotic lymph nodes. Furthermore, the kind of pathological variation can be determined automatically during segmentation, which is important for the automatic TNM classification.

Our technique was tested on 21 lymph nodes from 5 CT datasets, among several enlarged and necrotic ones. The results lie in the range of the inter-personal variance of human experts and improve the results of former work again. Bigger problems were only noticed for pathological lymph nodes with vague boundaries due to infiltrated neighbor tissue.

Keywords: Stable Mass Spring Models, Dynamic Models, Segmentation, Lymph nodes, CT data

1. MOTIVATION

The assessment of a tumor disease (TNM classification) and some other possibly necessary surgeries (neck dissections) depend on the lymph node situation (size, affection, infiltrations of neighbor tissue). Therefore, it is important for the computer assistance of tumor diagnosis and surgery planning to get this information. If exact analyses, visualizations or measurements should be made, the lymph nodes have to be segmented (e. g. in CT data), which, in general, is one of the most time-consuming steps.

2. STATE OF THE ART

In Rogowska et al.[1] several segmentation techniques are analyzed and it is stated, that reliable lymph node segmentation is only possible with a lot of model knowledge. The fast-marching technique of Yan et al.[2] needs heavy user interaction (barriers, etc.) for stable behavior. The active surfaces of Honea and Snyder[3] use more complex model knowledge, but were not evaluated on real data (only on idealized phantoms).

The first relatively robust method[4] uses a two front Stable Mass Spring Model (SMSM), which integrates shape and appearance knowledge and needs only a starting point very near to (normally inside) the structure to segment. The quality of the segmentation results lie only a bit above the inter personal variance. Enlarged, necrotic or unclear bounded lymph nodes were not addressed, even is very important for tumor diagnosis. Similar to this is a new technique[5] that uses a statistical instead of a Stable Mass Spring Model. This statistical model uses very few shape modes to restrict the model to rather elliptical shapes. The results of this method are only worse a little bit in comparison with the technique before, but a lot more of user interaction (rough drawing of the lymph node contors on the dataset) is needed before the segmentation and in some part a manual postcorrection is recommended.

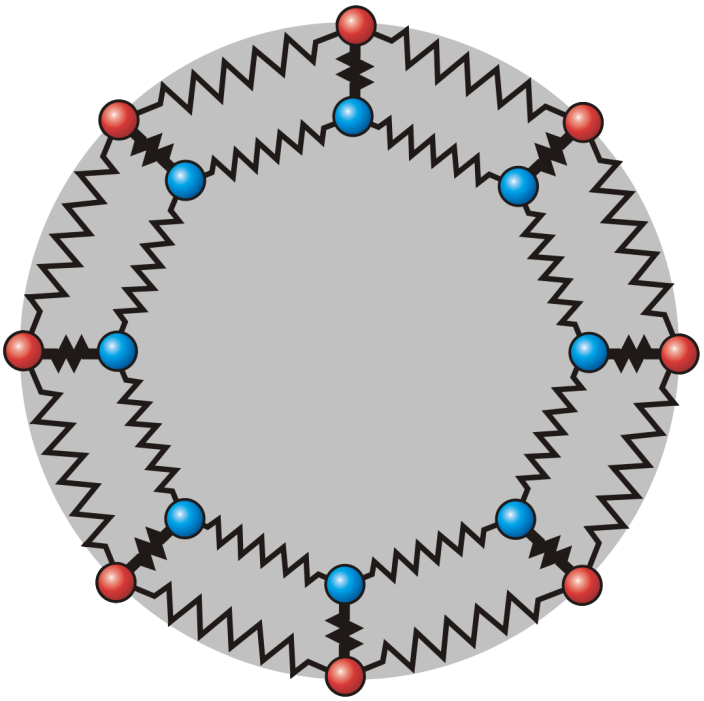


Figure 1: Schematic of the two front lymph node model (SMSM).

3. METHODS

We present a segmentation technique for lymph nodes in CT data, which extents the method from Ref. 4 considerably regarding exactness and support for enlarged, necrotic and substantially deformed lymph notes, which are of heavily application specific relevance (e. g. in the case of tumor diseases).

We use a Stable Mass Spring Model (SMSM[6]) for the segmentation of the lymph nodes. This model consists of two fronts or shells and is initially ball shaped (figure 1). Furthermore, it can deform elastically due to its physical nature to model the shape of real lymph nodes. The outer front has edge sensors at the mesh vertices, which strive to edges in the CT dataset with have an orientation parallel to the model's surface. In contrast to this, at the vertices of the inner front there are in intensity sensors, which strive into the typical gray value range of lymph nodes in CT datasets.

This way, when started inside a lymph node, the model adapts by physically-based movement and deformation controlled by its outer front to this lymph node's edges, while its inner front keeps the model keeps the model on the lymph nodes, so it cannot drift away or leak out. Meanwhile, the elastic acting shape preserving torsion forces of the Stable Mass Spring Models[6] make sure that the model keeps a rough lymph node shape according to the chosen weightings of dataset fitting and shape maintenance.

3.1. Plateau filtering

In contrast to the technique in Ref. 4, we filter the CT datasets (their intensities respective gray values) by means of plateau transformations, before the sensors of the model access them. In the case of the intensity sensors a transformation variant is used, which set the full lymph node Hounsfield range (1050 to 1100 in our datasets) to its base value 1050. All values below 1050 are not changed and all value above 1100 are flipped on the center value of the lymph node intensity interval, in our case 1075 (see figure 2).

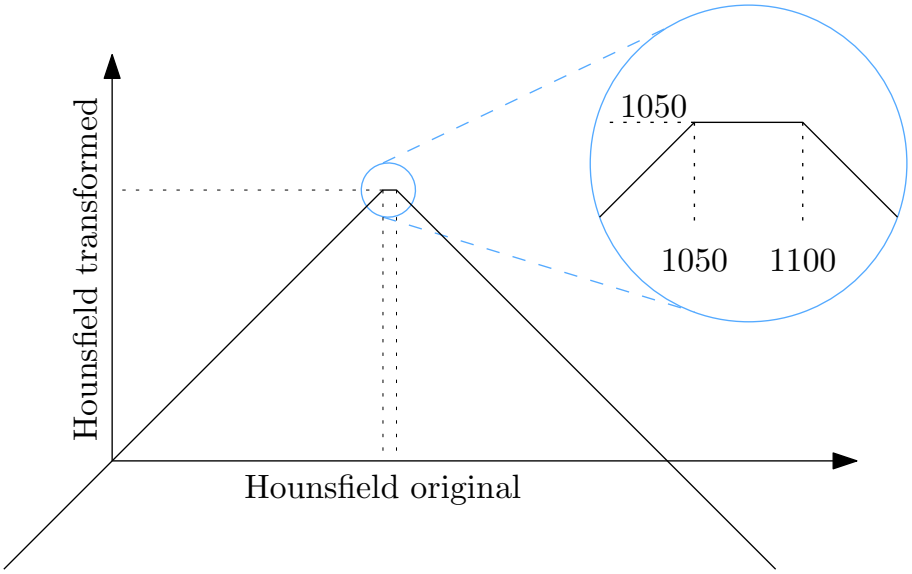


Figure 2: Schematic course of a plateau filter function.

This way, it is guarantied that all gradients in the dataset point in direction of the lymph node intensity range, which has no further gradients inside. So, all gradient-based intensity sensors strive into the lymph nodes, but create no disturbing and unwanted forces, when they are inside the lymph nodes.

Especially for necrotic lymph node (like in figure 3 and 4) this behavior is very important and a big improvement compared to the base method, because they have strong inner gray value variations, which normally would strongly disturb the model. If otherwise the gray value interval is filtered using rigid limits (rectangle-shaped function) like in the base method, then strong forces that deform the model too much will appear due to the very strong gradients at the filtered, binary gray value interval borders. Furthermore, there will be no forces outside the lymph nodes, which could pull back the intensity sensors back into the lymph node, if the have driven away too much. Also, if the gray value interval fits not perfectly to an individual lymph node, its borders could not be found exactly by the model if the lie slightly outside this interval, since the model will be held strongly inside this interval behind the binary, filtered gray value interval border (see figure 3 (b)).

The edge sensors use instead of the original dataset also a special, plateau-filtered dataset. This plateau transformation is different from the one used in the case of the intensity sensors in that way that the plateau is degenerated („pushed together“) to a peak at the top of the lymph node gray value interval, which is in our case 1100. So, this special case of the plateau filtering is done with a triangle-shaped function.

By this, it is achieved that the orientation of all edges in the dataset within the gray value range above 1100 is flipped, but their size and strength is not changed, so that no edges disappear and no edges develop by gray value interuptions caused by the filtering. So, after this plateau filtering the lymph node gray value range is the most intense in the dataset. Therefore, it can be assumed that all lymph node border edges are oriented (regarding their gradient) inside the lymph node („from dark to bright“), even if the were adjacent to a brighter, contrasted vessel in the original dataset (see a plateau-transformed dataset in figure 3 (a) in contrast to the original dataset in (b)).

This way, the edge sensors on the outer front can be adjusted to detect only border edges oriented inside discarding most of the useless, distracting edge information in the dataset without losing only an lymph node border edge. Otherwise, either the outside oriented edges had to be also considered, which would additionally distract the model, or, like in the base method, where also only inside oriented edge play a role, the edges to brighter neighboring structures were ignored and not found. In the last case, an unwanted drifting in this brighter structures then often happens (like in figure 3 (c)).

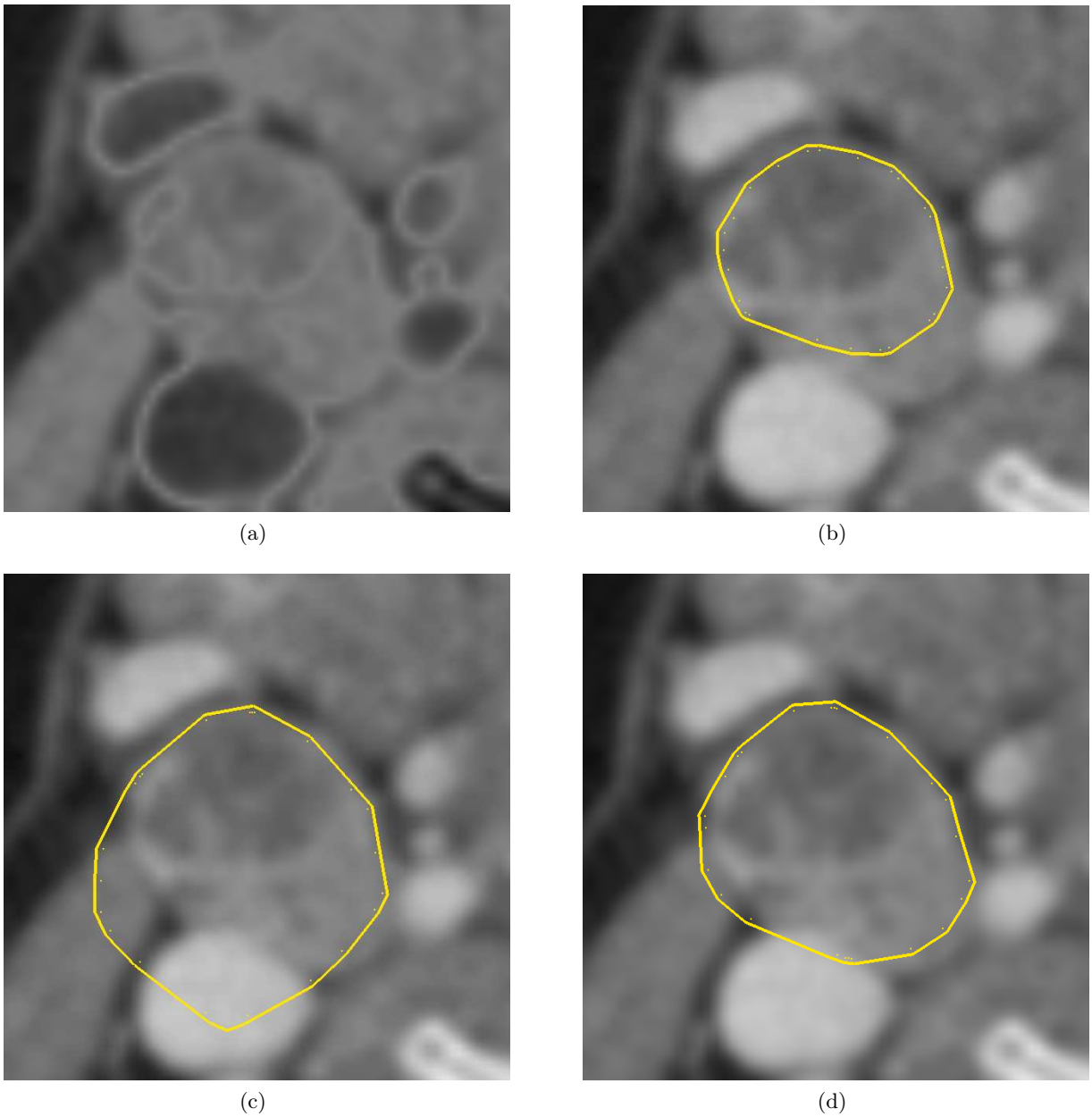


Figure 3: **(a):** plateau-transformed dataset. **(b):** model adaption using a rectangle-filtered gray value range for the intensity sensors. **(c), (d):** model adaption using plateau-filtered intensity sensors in (c) without and in (d) with plateau-filtering for the edge sensores

3.2. Multi model segmentation

If one wants to segment lymph nodes in general, it can be seen that lymph nodes can differ a lot. They can be small and large, elliptical and heavily deformed, evenly gray and strong textured, etc.. Especially lymph nodes relevant for tumor assessment are often enlarged, deformed or necrotic (strongly textured or at least with dark interior areas) and form from a computer vision point of view different classes of objects regarding to scaling, shape variation and texture (or appearance).

SMSMs are prototypical models, which are verifiable very well suited for the segmentation of such a class of

scaling factor	1	2	3	4	5	6	7	8	9	10
quality of fit	0.572	0.570	0.572	0.757	0.769	0.834	0.835	0.841	0.791	0.763
visual acceptable	no	no	no	no	no	yes	yes	yes	no	no
aver. sur. dist. (mm)	8.85	8.80	8.35	3.65	3.53	1.19	1.23	1.03	1.98	1.97
Tanimoto coefficient	0.012	0.012	0.046	0.428	0.445	0.733	0.731	0.760	0.620	0.591

Table 1: Results of the multi model segmentation with models of different scaling factors (base model: 3 mm diameter) on a dataset with large, necrotic lymph nodes (diameter: ca. 22 mm). Best results achieve the models of scaling factor 6, 7 and 8, which have an initial diameter of 18, 21 respective 24 mm.

objects (with specific shape and appearance and also scaling, if wanted). In contrast to this, in theory statistical models (ASMs, etc.) can represent different object classes at the same time, but practically they have also problems, if these classes differ to much from each other and there should exist no mixed classes in the modeling problem. However, for single classes special designed models perform better than general models, which also model other classes at the same time.

Hence, we use a set of single models in a concurrent segmentation strategy, each specially designed for a certain kind of lymph node. For the lymph node segmentation one of the most important class partition is the one by size. So, we began with a set of models for lymph nodes of different sizes (see figure 4). Furthermore, there are also models thinkable for different lymph node textures, shapes, etc..

For the multi model segmentation all models from the set will be started at the same position (normally set from a click inside a lymph node) in parallel. After the individual model adaption have converged and finished, the best fitting model of all started models is chosen as the segmentation result. So, besides the pure segmentation result it is also possible to determine the class of the segmented lymph node, because it is known, which model the results comes from.

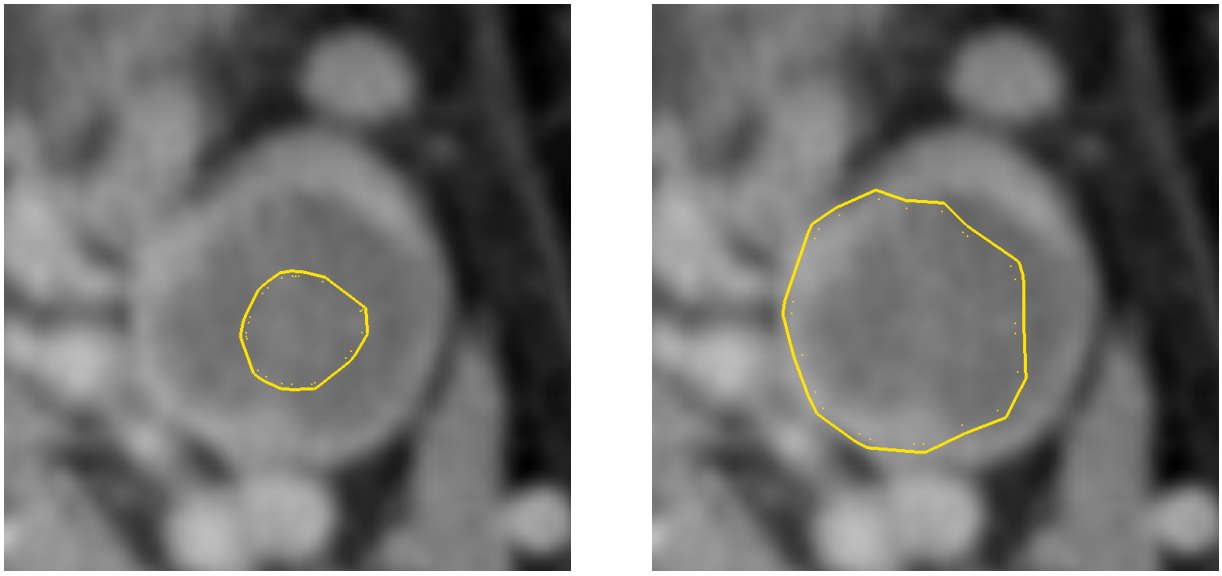
The best fitting model is determined using a quality of fit calculation, which considers both the corresponding of the adapted model to the dataset (using the current sensor values of the adapted model) and its deformation (using the still existing shape forces of the adapted model). The result is calculated as a value between 0 (not fitting) and 1 (very well fitting). Ref. 7 explains how the quality of fit can be calculated for SMSM, which are used in our method. Furthermore it states, that these models are especially suited for the calculation of such a quality of fit, which was one important reason to choose this model type for our segmentation task.

4. RESULTS

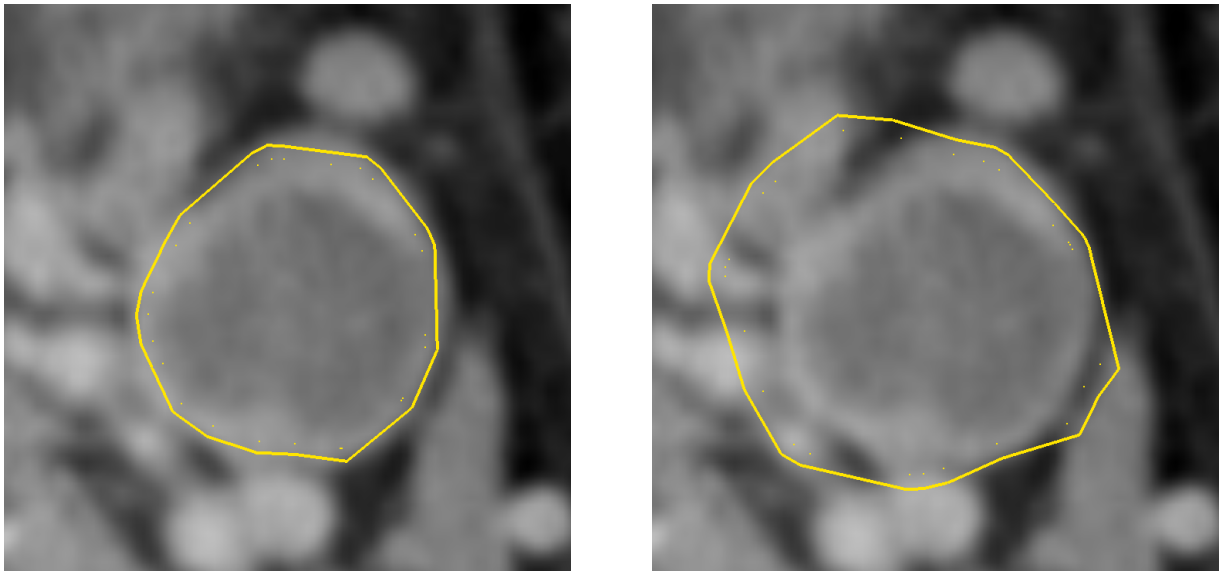
The experiments were carried out on 21 lymph nodes from 5 CT datasets from machines from three different manufacturers. They had slice distances from 1 to 3 mm and a resolution of 0.28 to 0.47 mm. An isotropic resampling (to the slice resolution) was necessary for the Stable Mass Spring Models, because their sensors rely on gradient computations, which need cubic voxels. Gold standard were expert segmentations additionally approved by radiologists.

The effect of the multi model segmentation technique was quantitatively evaluated using models of different scales (base model with 3 mm diameter and scalings of this model) on all four existent enlarged Lymphnodes (diameter $>$ 10 mm) in the given datasets. Table 1 shows the results in the case of an especially large, necrotic lymph node (diameter: approximately 22 mm) exemplarily, which are principally very similar to the other results. Here, it can be seen that a high quality of corresponds very well with a good segmentation.

Table 2 shows the results of the complete evaluation. Here, the segmentations of the human experts are compared the base method from Ref. 4 and the newly developed method from this paper. In contrast to the base method, the new one performs 23 % better in average (regarding the surface distance) and even improves the results of the human experts slightly.



(a) (b)



(c) (d)

Figure 4: results of the multi model segmentation using modes of different scaling level: **(a):** factor 3, **(b):** factor 5, **(c):** factor 7, **(d):** factor 9

5. CONCLUSION

The presented technique for the semi-automatic segmentation of lymph nodes in CT-Datasets is the first, which can handle lymph nodes of different classes (enlarged, necrotic) with only minimal interaction effort (on click in the lymph node center). The quality of the results improves the former techniques and lies in the range of human experts. The running time of only a few seconds qualifies the presented method for use in clinical environment. Anyway, complicated deformations or big necroses cannot be segmented satisfying in any case, because it is possible that too much dataset information (artifacts, poor dataset quality, etc.) is missing to be completed by the model knowledge.

method	expert 1	expert 2	base method[4]	new method
aver. sur. dist. (mm)	0.418	0.442	0.535	0.412
Hausdorff dist (mm)	3.258	3.243	3.514	3.153

Table 2: comparison of the segmentation results of all 21 lymph nodes by two human experts, the base method[4] and the here presented method

The introduced plateau filterings could also be interesting for other sensor-based segmentation models, because general problems are addressed with them (object internal gray value range and useless, distracting edge information). Also interesting in this way could be the principle of the multi model segmentation, which effect was theoretical motivated and practical clearly confirmed. Here, a transfer to other segmentation problems with different object classes is also to consider.

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