Vessel Extracting Gas – Using self organization in the extraction of vascular trees

Dietlind Zühlke
Fraunhofer Institute of Applied Information Technology FIT
Mailing address
email: dietlind.zuehlke@fit.fraunhofer.de

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Abstract— A network model is introduced that allows the extraction of the topological structure of a set of input vectors corresponding to a vascular tree in a 3D Doppler or contrast enhanced ultrasound. This extraction is a precondition for many medical image registration algorithms. The method is based on the Growing Neural Gas algorithm (GNG) by Fritzke [1]. The GNG network model is extended by introducing a sphere of influence for each vertex to represent the width of the vessel. Results on artificial and real ultrasound image data sets are discussed.

1 Introduction

One objective of our research team is to develop an intervention assistant[1] for navigation supporting the local tumor therapy in liver tumors. A near real time registration between a pre-interventional tomographic image and an interventional 3D ultrasound (US) image data set is crucial for this purpose.

Registration in this field means transforming the coordinate space of one image into the coordinate space of the other image [2]. After this transformation both images can be aligned or even merged. This way information in one image modality can be joined with the information available in the other. In the given application this means, that the registration procedure has to merge the data sets accurately enough that the physician can intuitively map radiological information onto pertinent regions in the US.

According to Aylward et al. [3] there are three basic forms of image registration:

- image-image registration
- image-model registration
- model-model registration

The choice of the procedure depends on features of the image data, e.g. the visibility of anatomical structures.

The current clinical procedure is based on an interactive landmark based registration of external bony landmarks. This method is error prone and slow if many adjustments have to be made. The objective was to develop a registration method that is more stable, more accurate and faster.

[1]the LOCALITE SonoNavigator

The following considerations influenced the design of the new registration process:

- Image-image registration is rather slow, because much basic image information, in the majority of cases color- or gray values, is used for the algorithm. This approach is used for images with similar image features, such as similar gray values in same image modalities. It is not suitable for images of low quality (noisy and with artifacts), because convergency is slow and the probability to hang in a local minimum is high.
- Image-model and model-model registration both use reduced image information. These approaches are faster if this reduced information is already available. These registration methods yield unacceptable results if information loss is produced by an inadequate reduction.

To apply the image-model or model-model principle approach, a stable and geometrical valid model of one (or both) of the image data sets has to be produced in a first step. Therefore only structures can be exploited, that can be seen in both image data sets and that are stable with respect to deformation. In our case, the blood vessels are a structure that is in this sense useful for registration of soft tissue images. The topological structure defined by the branching points as well as the radius of the vessels are the two features that are not influenced by soft tissue shifts. They are therefore pivotal features. Other features such as length or direction are affected by tissue shifts.

The vascular tree models have to be derived from two different image modalities:

(1) tomographic image data sets (MRI, CT)

(2) 3D Doppler or contrast enhanced ultrasonic image data sets

The blood vessels are extracted from the tomographic data using a segmentation-based method [4]. We developed an extraction method for 3D Doppler or contrast enhanced ultrasound image data sets. A model of the blood vessel system is extracted through self organization.

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2 Methods

In the following section, related work from the field of extracting models from images is shortly discussed and the developed algorithm will be related.

The method has to realize an extraction of a model for the blood vessel system of a region of interest within the patient's liver from a 3D ultrasound image data set. The result has to be a graph with edges that have the additional attribute "radius" corresponding to the radius of the modeled vessel.

2.1 Related work

Usually the extraction of vessel trees is achieved by segmentation-based methods (Region Growing [5]; combination of "traversal, iterative refinement, and voxel labeling" [6]). These algorithms strongly depend on the image quality. Such methods are successfully applied [6] to computer tomographic data that is much less noisy than ultrasound. If those methods are used for US images (e.g. [5]), manual corrections have to be introduced after the automatic processing. The segmentation-based methods suffer from exclusively using color- or gray value information.

Learning based methods can additionally consider structural information. They are successfully used for fast and robust extractions of models ([7, 8]). That makes them suitable for the given application. An algorithm for learning was sought that allows a fast and robust estimation of the topology of a given structure. To realize this so called "Topology Learning" [1], there are methods available for a wide range of applications. For an overview on topology representing networks see [9].

A basic approach for "Topology Learning" is the Neural Gas by Martinetz and Schulten [10]. It extracts a graph structure with nodes and edges from feature spaces with arbitrary dimensions. In the given application the feature space is the 3D image data. The method has one major drawback for our application: the number of adaption steps has to be specified in advance. In our application the number of adaption steps needed for a good performance strongly depends on the size of the structure that is to be extracted. This size is not known in advance.

To overcome the problem of a fixed number of adaption steps Fritzke introduced a modification of the NG – the Growing Neural Gas [1]. Adaption now stops if a specified performance criterion is met. The Growing Neural Gas algorithm (GNG) is particularly suited "to learn the important topological relations in a given set of input vectors by means of a simple Hebb-like learning rule" [1]. Again the result is a graph structure with nodes and edges. But this structure does not entail information on the diameter of the structure.

An extension of the GNG, the Active Balloon Model [7], was introduced to calculate a complete three-dimensional model of a given structure including information about radius. At first a skeleton is calculated from a set of points at the surface of the structure by a modified GNG. After that, a representation of the shape is extracted via Active Balloons. There are two problems with this method in our application:

(1) The result is a model of the object as a polygonal representation composed of surface points. Because we need a model consisting of nodes and edges with a radius, additional calculations would have to be made.
(2) The extraction of the skeleton and the real volume shape extraction (including radius) are separated. The runtime behavior of this method is not suitable for real-time applications.

For the given application a combined extraction of skeleton and shape including radius is required. Therefore an algorithm based on GNG was developed, that builds up both types of information during the learning process. The Growing Neural Gas algorithm by Fritzke was adapted and expanded for the extraction of vascular models. The developed Vessel Extracting Gas (VEG) algorithm will be explained in detail in chapter 2.3.

2.2 Limitations using GNG in the given application

The neural network shall extract the following vessel features:

- topological structure defined by the branching points
- diameter

In a first attempt the original GNG was applied to the given data as follows:

- *training vectors:* positions of those voxels in the 3D ultrasound image data set that according to their gray value are likely to belong to the vessels, so called "vessel voxels"
- *initialization:* two vertices placed at a random place in the 3D ultrasound image data space with a joining edge

For the original GNG algorithm by Fritzke [1], the following problems became apparent during the learning process:

(1) *Overrepresentation of large vessels*
(2) *Difficult diameter estimation*
(3) *Connection of unconnected vessel parts*

Figure 1(a) shows the surface of a vessel voxel set which is to be modeled using the GNG. The result is given in figure 1(b), it illustrates the problems (1) and (2).

In the following the reasons will be explained in detail. In chapter 2.3 modifications of the algorithm to tackle the problems are introduced.

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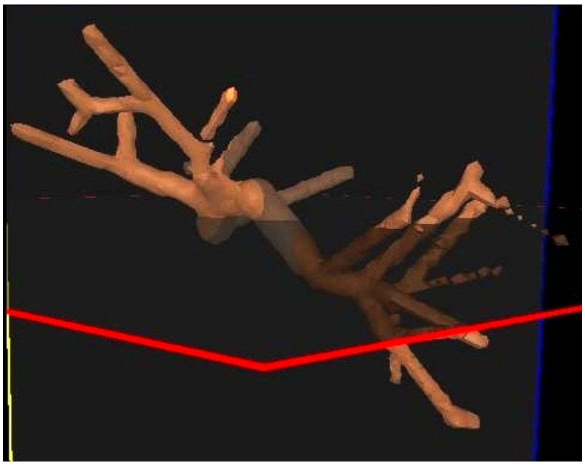
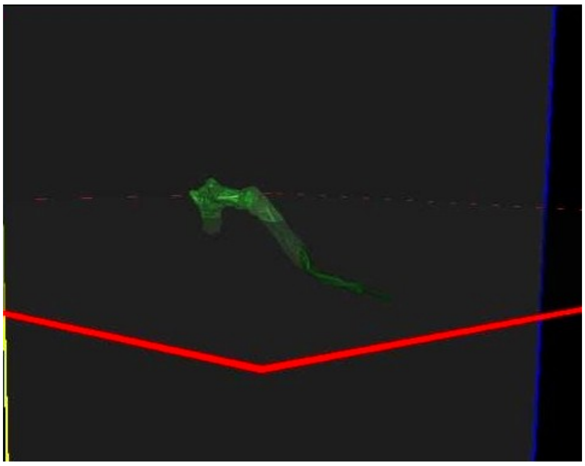


(a) Vessel voxel set taken from the ultrasound, *yellow:* Surface of the vessel voxel set taken from an artificial 3D ultrasound volume.



(b) GNG after learning process on the vessel voxels shown in figure 1(a), *green:* GNG structure with overrepresentation of larger vessels whereas smaller vessels are nearly not represented.

Figure 1: Problems using GNG

2.2.1 Problem 1 – Overrepresentation of large vessels

Vessels with a large diameter are overrepresented with vertices, whereas smaller vessel are completely unrepresented. The reason for the unequal representation is the error accumulation. Larger vessels contain more vessel voxels. That means it is more likely that a vessel voxel of a large vessel is presented to the net than a vessel voxel of a small vessel. Thus vertices representing areas of large vessels are hit more often than those representing smaller areas. That is the reason why a larger error value is accumulated in the area of larger vessels and many new vertices are added there. In the area of small vessel the accumulated error value is small in comparison, because training vectors of those areas are seldom presented. So nearly no vertices are added here.

This problem is known as the "magnification property" of the Neural Gas [11]. One simple approach to overcome this problem is the "conscience" introduced by deSieno [12]. Here every vertex has a bias based on the number of times it was the winning vertex. This bias term is incorporated into the competition. A vertex "that wins too often begins to 'feel guilty' and prevents itself from winning excessively"[12].

Another possibility to cope with the problem was developed by Der and Herrmann [11]. Here the learning rate for the winning vertex is adapted taking the local density of the input vector room near this winning vertex into account. Both approaches lead to a positioning of the vertices that is equally distributed in the input vector room. This way they are able to solve the first problem but the second one, diameter estimation, is still open.

2.2.2 Problem 2 – Difficult diameter estimation

To develop a model of the vessels that is useful for registration, an estimation of the diameter of the vessels is needed. It is possible to estimate the diameter from the result graph calculated by the GNG. A vast number of vertices would have to be inserted to get a representation of the small vessels. Some kind of center line recognition and radius estimation would be needed. This conceivable estimation is complex and in conflict with the real time requirements.

2.2.3 Problem 3 – Connection of unconnected vessel parts

A further problem that became evident during the tests are inappropriate connections of vertices of the GNG without correspondence in the real data. The edges of the GNG do *not* reliably identify vessels. The main reason is that besides "nearness" there is no other structural feature exploited such as continuity. Therefore, different but close vessels are often merged.

2.3 Vessel Extracting Gas – VEG

The Vessel Extracting Gas procedure is initiated like the GNG by placing two vertices at a random place in the input space that get a joining edge. As training vectors the vessel voxels are presented to the net.

2.3.1 Modifications to solve the problems overrepresentation and missing diameter estimation

A combined solution for both problems is introduced to the network through the addition of a further attribute that is assigned to the vertices in the VEG. We call it "sphere of influence" r in R.

If a model of the vascular tree extracted from the tomographic images is given, the sphere of influence is initialized with the average radius of the vessels in this model. As a new process step the width of the sphere of influence of every single vertex is adapted during every learning iteration. According to the "Winner-takes-all" principle (see

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e.g. [13]) this adaption is applied to the vertex that is nearest to the input vector, called ”Winner”.

- If the presented input vector lies inside the sphere of influence of the Winner vertice, its sphere of influence is decreased.
- If it lies outside, i.e. its distance to the vertices position is larger than the radius of the sphere of influence, the sphere will be increased.

The adaption rules for the sphere of influence are shown in table 1.

Condition	Adaption rule
$\|d\| > 2r$	$\Delta r = \epsilon_w \cdot 2 \cdot y_{max}$
$2r \geq \|d\| > r$	$\Delta r = \epsilon_w (y_{max} \sin(\Pi \frac{d}{r} + \frac{\Pi}{2}) + y_{max})$
$r \geq \|d\|$	$\Delta r = \epsilon_w (y_{min} \sin(\Pi \frac{d}{r} + \frac{3 \cdot \Pi}{2}) - y_{min})$

Table 1: Adaption rules for the sphere of influence of the VEG for distance d

After the learning process, the sphere of influence encloses those points in the ultrasound volume, that lie near the vertex and that are vessel voxels according to their gray value. That gives a useful estimation for the radius of the vessel. This is a solution for the problem of *diameter estimation* that is in accordance with reality and easy to calculate.

According to Fritzke [1], a new vertex is added near the vertex with the highest error value. So to overcome the problem *Overrepresentation of large vessels* the sphere of influence is integrated into the error accumulation by means of a case differentiation as follows:

- If the input vector lies inside the sphere of influence, nothing is added to the local error counting variable.
- If the vector lies outside the sphere of influence, the squared distance is added as suggested by Fritzke [1].

For a vertex representing an area of a large vessel, the sphere of influence will grow according to the adaption rule in Table 1. Thus many presented vessel voxels will lie inside the sphere. For those vessel voxels an adaption is made, but nothing is added to the local error counting variable. Thus new vertices are not created in this area. This mechanism can prevent large vessels from being overrepresented.

2.3.2 Modification to solve the problem of inappropriate connections

To address the problem of *Connection of unconnected vessel parts*, an assessment for edges was integrated into the learning process. It is based on the mean gray value of the edge. This value is calculated by averaging the gray value along the line between the two endpoints. If it lies beyond the adjusted threshold for the vessels, the construction of the edge is rejected.

During the learning process the topological structure is adapted as in the GNG via the age system of the edges [1]. Every edge d has a counter age_d that is increased if one of the adjacent vertices is the Winner vertice. If a certain edge is ”older” than the maximum age for edges a_{max} it is removed. Thus changes in the topology of the network by adaptation of the adjacent vertices are taken into account. As a stopping criterion, a final network size that has to be set in advance was used. In chapter 2.4 the influence of the final network size is discussed.

The result of the introduced method is a graph structure, with the additional attribute ”sphere of influence” for the vertices. From this extended structure, the vascular tree model can be calculated by giving each edge a radius that is the mean width of the sphere of influence of its endpoints.

2.3.3 Elements of the VEG

The elements of the VEG are presented in accordance to the pertinent description of the GNG algorithm. Differences to the original network configuration by Fritzke [1] are marked in bold-faced type.

The network for the Vessel Extracting Gas:

- a set of vertices A, with $c \in A$ has:
  - an n-dimensional reference vector $w_c \in R^n$, that can be seen as position in input space
  - a local counting variable $error(c) \in R$, to accumulate the error value
  - **the sphere of influence** $r_c \in R$
- a set of edges N, with $d \in N$ has:
  - a pair of vertices $\{c_1, c_2\} : c_1, c_2 \in A$
  - an integer age $age_d \in Z$
- a set I of n-dimensional input signals (training vectors) **from the ultrasound volume's space**, with $\xi \in I$ representing a probability density function $P(\xi)$

2.3.4 Process steps of the VEG

Here in addition to the structural elements the actual procedure is described. The complete VEG algorithm is shown below. The differences to the original GNG algorithm by Fritzke [1] are marked in bold-faced type.

Vessel Extracting Gas algorithm:

(1) Initialize the network with two vertices a and b at random positions w_a and w_b in R^n, **spheres of influence** r_a **and** r_b **respectively and an edge** v **between** a **and** b**.**

(2) **Present a randomly chosen point** ξ **from the set** I **of vessel voxels.**

(3) Find the nearest vertex s_1 as well as the second nearest vertex s_2.

(4) Increment the age of all edges adjacent to s_1.

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(5) **If ξ lies outside the sphere of influence of s_1, i.e. $|w_{s_1} - \xi| > r_{s_1}$,** add the squared distance in the input space between the input signal and the nearest vertex to the local error value:
$\Delta error(s_1) = |w_{s_1} - \xi|^2$

(6) Move s_1 and its topological neighbors (in the graph) towards ξ by fractions ϵ_b and ϵ_n, respectively, of the total distance:
$\Delta w_{s_1} = \epsilon_b(\xi - w_{s_1})$
$\Delta w_n = \epsilon_n(\xi - w_n)$ for all direct topological neighbors n of s_1

(7) **Adapt the sphere of influence of vertex s_1 according to the rules given in table 1.**

(8) If s_1 and s_2 are connected via an edge, set the age of this edge to zero. If such an edge does not exist, create it **as far as its mean gray value exceeds the threshold for vessels.**

(9) Remove edges with an age larger than a_{max}. If this results in results in points having no emanating edges, remove them as well.

(10) If the number of input signals presented so far is an integer multiple of the parameter λ, insert a new vertex as follows:

- Determine the vertex q with the maximum accumulated error.
- Insert a new vertex t half way between q and its neighbor f with the largest error variable:
  $w_t = 0.5 \cdot (w_q + w_f)$.
- Insert new edges between t and q and t and f, **as far as their mean gray value exceeds the threshold for vessels,** remove the original edge between q and f.
- Decrease the error variables of q and f by multiplying with the constant α. Initialize $error(t)$ with the new value for the error variable of q.
- **Initialize the sphere of influence of the new vertice:**
  $r_t = 0.5 \cdot (r_q + r_f)$

(11) Decrease all error variables by multiplying them with the constant d.

(12) If the number of vertices is smaller than n_f, go back to step 2.

2.4 Determining an appropriate parameter set

As in any other learning method, the choice of the parameters is crucial for the performance of the method. Thus the determination of an appropriate parameter set is very important.

To optimize the parameter set, a test environment was built that permits qualitative evaluations of the results. It shows image volumes and vascular tree models respectively from the tomographic data as well as from the ultrasound data. The image volumes are displayed as derived surface models with an adjustable threshold (see figure 2(a)). The extracted vascular tree models are displayed as combinations of spheres and cylinders (see figure 2(b)). It is possible to qualitatively evaluate the topological adequacy of the extraction by simultaneously displaying the surface model and the extracted vessel model or by switching between both of them.

The parameter optimization tests were first run on artificial ultrasound image data sets. To create these test data, a set of vessel tree models was taken, that was extracted from an MRI of a proband study by MeVis GmbH. The models are given as sets of vertices and edges with extracted diameters.

From these models artificial 3D Doppler ultrasound volumes were created as follows: The model was transformed to fit into a volume data set of a fixed size. Then gray values corresponding to typical Doppler ultrasound gray values were introduced into the artificial volume data set at the positions specified by the transformed model. The artificial data did *not* include the following characteristics of normal 3D Doppler or contrast enhanced ultrasound (see e.g. [14]):

- noise
- speckle
- artifacts

To initialize the Vessel Extracting Gas algorithm the following parameters have to be introduced:

- threshold for vessels θ
- maximum age for edges a_{max}
- learning rate for the reference vector of the Winner vertex ϵ_b
- learning rate for the reference vector of topological neighbors ϵ_n
- learning rate for sphere of influence of the Winner vertex ϵ_w
- error decrease factor for adapted vertices α
- error decrease factor for all vertices d
- number of iterations until a new vertex is inserted λ
- final net size n_f

The threshold for the vessels determines the set of vessel voxels.

To identify a good set of parameters the procedure was first started with the values used by Fritzke in the GNG [1]:

- maximum age for edges $a_{max} = 50$,
- learning rate for winner reference vector $\epsilon_b = 0.2$,
- learning rate for neighbor reference vector $\epsilon_n = 0.006$,
- error decrease factor for adapted vertices $\alpha = 0.5$,
- error decrease factor for all vertices $d = 0.995$,
- number of iterations until new vertex $\lambda = 100$.

To choose the learning rate for the sphere of influence, the value of the learning rate of the reference vector for the Winner vertex was used in a first attempt. To avoid extensive calculation times a final net size of $n_f = 10$ was chosen.

The following parameters had to be adjusted: a_{max}, ϵ_w, λ, n_f. The influence of the parameters on the performance of the VEG is summarized in table 2. The parameters α and d are not included in this table because their variation did not lead to a significant change in the results.

The following set of parameters yielded good results on artificial ultrasound image data sets checked in the test environment described above: $a_{max} = 125$, $\epsilon_b = 0.2$, $\epsilon_n = 0.006$, $\epsilon_w = 0.1$, $\alpha = 0.5$, $d = 0.995$, $\lambda = 2500$, $n_f = 20$.

parameter	too small	too large	recommended value
θ – threshold for vessels	prone to noise, vertices outside the vessels	few vessel voxels, concentration on large vessels	
a_{max} – maximum age for edges	loose structure	edges outside the vessels	125.000
ϵ_b – learning rate for winner's reference vector	small movements, slow convergency	large movements, slow convergency	0.200
ϵ_n – learning rate for neighbor's reference vector	neighborhood less impact, less structure	slow convergency, because of being pulled to and fro between neighbors	0.006
ϵ_w – learning rate for winner's sphere of influence	adaption too small, error accumulation and problems similar to GNG	too large spheres of influence	0.100
λ – number of iteration until new vertex	error accumulation not representative, bad positioning of vertices	very long running time	2500.000
n_f – final net size	underrepresentation of small vessels	overrepresentation of large vessels, long running time	20.000

Table 2: Results of parameter tests for the Vessel Extracting Gas approach in test environment

2.5 Results of the VEG

There are two criteria for the evaluation of the extraction method:

- *The appropriate modeling of the vascular tree:* This can only qualitatively be judged because there is no measure of a good extraction. Bad extractions can be characterized by over- or underrepresentation of vessel parts, by vertices or edges outside the vessels or widths of the calculated edges that do not model the real radius of the vessel (see e.g. figure 1(b)). Good extractions are characterized by a proper presentation of all vessel parts, by a central position of vertices and edges inside their corresponding vessel part and a width fitting the radius of the vessel (see e.g. figure 3(c)).
- *The time performance of the method:* In the application described in section 1 the calculation has to be nearly real-time. The VEG was tested on a PC with Intel Pentium D CPU (two processor kernels with 3.00 GHz resp.), 2.0 GB RAM under Windows XP with Service Pack 2. The given running times apply to this PC.

2.5.1 Results on artificial data

Tests of the VEG on different artificial data sets (see above) were run. An example result shown in figure 2 was calculated with the set of parameters given in table 2. The width of an edge was calculated as the average width of the spheres of influence of both adjacent vertices.

For all tests the following extraction properties were found:

- The width matches with the vessels radius.
- There are no vertices or edges outside the vessels.
- Smaller vessels are underrepresented.

Average extraction time was 3 s. This is fast enough for the target situation.

2.5.2 Preliminary results on real data

Additionally first tests on different real US data sets have been run. The data sets have been 3D ultrasound images (Doppler or contrast enhanced) and vascular tree models derived from the 3D MRI or CT data set. They were recorded in a proband study as well as in real clinical applications. The VEG was used to extract the vascular tree from the US data. The results were visually controlled.

The parameter set identified in tests on artificial data (see chapter 2.4) could be used without deeper changes, except the final net size. Because the data had a smaller volume the final net size had to be reduced.

The results shown in figure 3(b) and 3(c) were calculated with the parameter set $a_{max} = 125$, $\epsilon_b = 0.2$, $\epsilon_n = 0.006$, $\epsilon_w = 0.1$, $\alpha = 0.5$, $d = 0.995$, $\lambda = 2500$, $n_f = 15$. The extraction and calculation of the model took 1.776 s.

Other sample results are shown in figure 4(b) and 4(c). They were calculated with the parameter set $a_{max} = 125$, $\epsilon_b = 0.2$, $\epsilon_n = 0.006$, $\epsilon_w = 0.1$, $\alpha = 0.5$, $d = 0.995$, $\lambda = 2500$, $n_f = 9$. Only the final net size was reduced because the vessels in the US image were smaller. The extraction and calculation of the model took 1.094 s.

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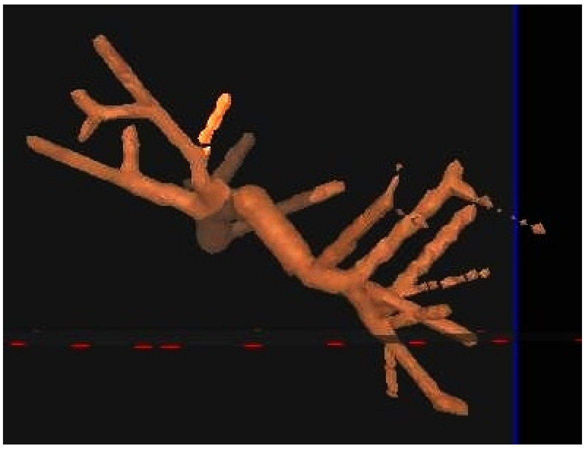
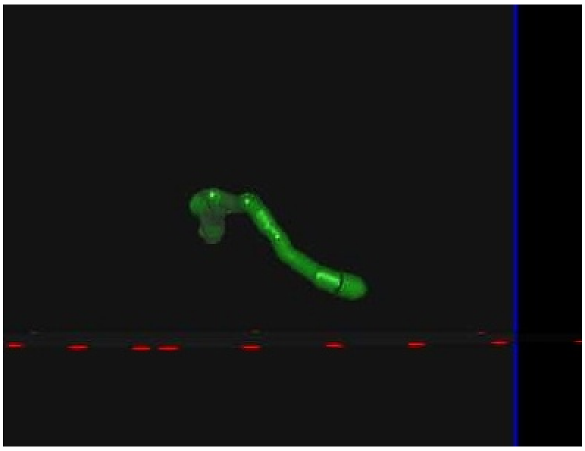


(a) set of vessel voxels, *yellow:* surface of the set of vessel voxels from the artificial 3D ultrasound image data set



(b) Vessel Extracting Gas model, *green:* portal venous vessel tree model from the Vessel Extracting Gas

Figure 2: Results of the Vessel Extracting Gas on artificial data

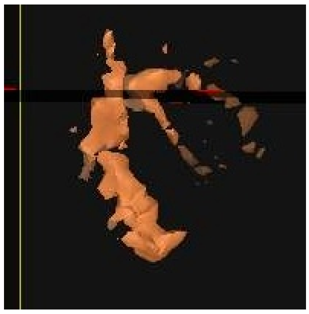
In all tests there were no vertices outside the vessels, but some inappropriate edges ran through areas not belonging to a vessel. The radius of the vessels almost matches the width of the edges. All parts of the vessels were represented, there was no over- or underrepresentation.

The average extraction time was 1.7 s, acceptable for the given application.

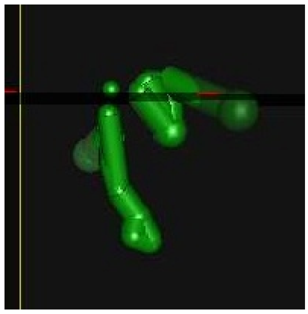
3 Discussion

According to first results on real data VEG seems to be stable against the typical distortions in 3D Doppler or contrast enhanced ultrasound (see e.g. [14]). The extraction of the vascular tree model is, according to the criteria mentioned above, acceptable and fast. Further testing on real data is needed.

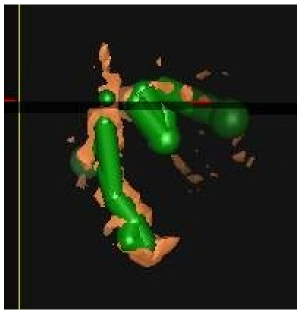
The successful application of this method to real medical image registration will require that one fixed parameter set can cope with most of the data. Otherwise the parameters



(a) set of vessel voxels, *yellow:* surface of the set of vessel voxels from a 3D proband's contrast enhanced ultrasound image data set



(b) Vessel Extracting Gas model, *green:* vascular tree model from the Vessel Extracting Gas



(c) Vessel Extracting Gas model merged with set of vessel voxels, *green:* vascular tree model calculated by Vessel Extracting Gas, *yellow:* surface of the set of vessel voxels from a 3D proband's contrast enhanced ultrasound image data set

Figure 3: Results of the Vessel Extracting Gas on real data

have to be adjusted for every single image. In this case it is important to know what adjustments have to be made for what kind of image data. First tests indicated the presented parameter set to yield acceptable results. Only the final net size has to be adjusted according to the size of the vessels given in the US image data.

The quality of extraction must furthermore be evaluated in the context of the authentic registration process if it shall be used in the medical target domain. Here the important criteria are relevant improvement compared to the interactive landmark based registration and a reduction of registration time.

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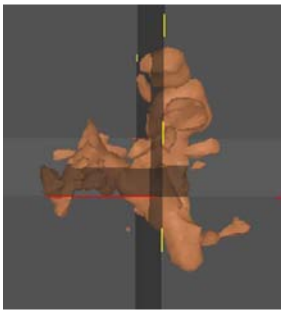
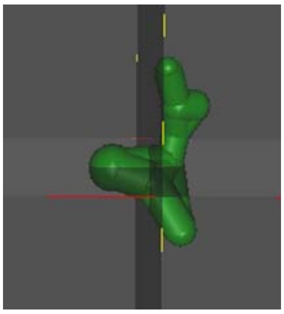
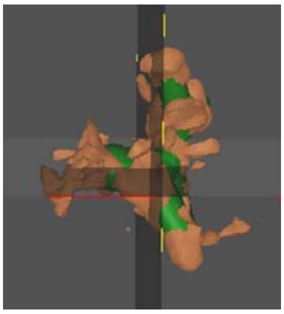


(a) set of vessel voxels, *yellow:* surface of vessel voxels from patient's 3D contrast enhanced ultrasound image data set



(b) Vessel Extracting Gas model, *green:* vascular tree model from the Vessel Extracting Gas



(c) Vessel Extracting Gas model merged with set of vessel voxels, *green:* vascular tree model calculated by Vessel Extracting Gas, *yellow:* surface of vessel voxels from patient's 3D contrast enhanced ultrasound image data set

Figure 4: Results of the Vessel Extracting Gas on real data

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