LEVEL SET BASED SEGMENTATION OF THE DISTAL FEMUR FROM 3D ULTRASOUND VOLUME IMAGES

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INTRODUCTION

Computer assisted surgery can improve accuracy and precision in many surgical techniques (Stiehl2005, Jenny2005). Moreover, imaging based computer assisted procedures allow for planning and visual control during all steps (Victor2005). Often, computed tomography (CT) and magnetic resonance imaging (MRI) are used as imaging modalities. CT offers good image quality but due to its ionizing radiation it is an invasive method. Also, soft tissue is poorly visible in CT data. MRI is affected by distortions (Moro-oka2007) and it is a quite expensive imaging modality.

Ultrasound offers high resolution images in real-time while being noninvasive, cost-efficient and broadly available. Its weaknesses, however, are a low signal to noise ratio (SNR), speckle, low contrast, acoustic shadowing and a small field of view (cf. Noble2006). Thus, new methods must be developed to extract and collate the relevant information from ultrasound data. We developed a new protocol and algorithm to segment the bony surface from ultrasound volume images. The applicability of our approach is demonstrated on distal femur surface reconstructions.

MATERIALS AND METHODS

Data Acquisition

Various 3D ultrasound volume images of the distal femur were acquired using the *Ultrasonix SonixTOUCH Research* system in combination with the linear array transducer 4DL14-5/38 (14 MHz). The image data was stored as a series of 2D raw images which then were scan line converted to obtain volume images in Cartesian space. In total, 19 images of a solid foam bone phantom (*SAWBONES*) and 47 images of a human knee (30-year-old male) were recorded.

Preprocessing

The logarithmic compression of the B-mode images was reverted by using a homogeneous point operation. Speckle and Gaussian noise was reduced by applying an edge preserving median filter.

Segmentation

The bone surfaces were extracted in a multistage process employing level set methods. The basic idea behind this is that due to acoustic shadowing the area below a bone surface has low intensity values and thus, expanding a curve from inside yields the surface. Jain and Taylor (Jain2004) showed that the exact bone surface is expected to be located between the point of highest gradient and highest intensity of a given intensity profile. Accordingly, in the final stage the segmentation result is refined using a level set approach based on a ridge detector (cf. Hacihaliloglu2008). The stages as seen in figure 1 are now described in more detail.

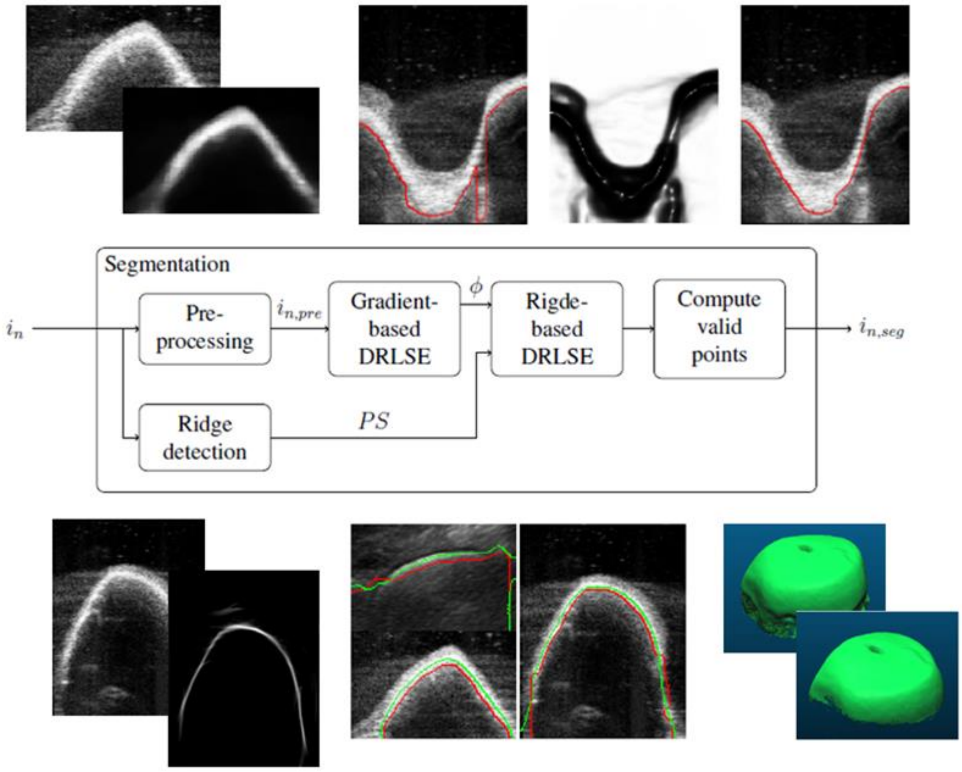

Figure 1: Stages of the level set based segmentation process of 3D ultrasound images. The images in the top row show a slice of an original volume image, its preprocessed image, an initial level set on an original image slice, its edge indicator function and the result of the gradient based DRLSE (from left to right). The bottom row shows a slice of an original volume image, the response of the ridge detector, initial level sets (red) on their original images and their refinements (green) and the resulting surfaces before and after removing uncertain surface points (from left to right).

In the first stage, initial level sets were estimated from the Cartesian images. This was done by traversing them column-wise and bottom up and while doing so writing back the hitherto found maximum intensity values. These transformed images were binarized by thresholding and then morphologically filtered. Empty columns, e.g. due to gaps, were removed. Finally, the binary images were mapped to the values minus one and one which correspond to the inner and outer area, respectively. As a result, initial contours lying inside the bones were obtained.

In the next stage, these initial contours were optimized using a distance regularized level set evolution (DRLSE) algorithm (Li2010). We used the same edge-based active contour model as described in the article by Li et al. except for an additional constraint we added. The level sets were only allowed to evolve in relevant areas which were determined automatically. The reason for that is that an unconstrained level set evolution would enclose the intensity profile of the bone surface if the structure did not fill up the entire image. The relevant areas were defined as the sets of columns that carried the initial level sets.

In the last step, the evolved level sets were refined using a ridge-based DRLSE. Again the algorithm of Li et al. was used, however without any area term and with a ridge indicator function instead of an edge indicator function. The ridge indicator function was built up from the result of an intensity invariant 3D local phase symmetry filter based on 3D Log-Gabor filters as described in (Hacihaliloglu2009). In their work, the orientation was estimated using the Radon transform since primarily straight structures were investigated. Due to the ever changing curvature of the femoral bone surfaces the orientation estimation was accomplished using the structure tensor (cf. Aach2006). Since the LSE approach produces closed surfaces some points did not lie on the actual surfaces. These points were filtered out simply by comparing their grey level intensity values against a threshold.

Validation

The resulting patches of the segmentation process for the bone phantom and the human knee were compared to ground truths obtained from CT (phantom) and MRI (human knee) scans, respectively. The rough alignment was done manually and the fine registration was done by applying the iterative closest point algorithm. The validation was carried out in (CloudCompare2014).

RESULTS

The reconstructed surface patches obtained from the segmentation of the bone phantom looked correct; fine details like small bumps and cavities were present. However, one of the patches exhibited a small extraneous segment in the border area which was removed. With this, the average distance error of all bone phantom patches was 0.30 mm ± 0.37 mm. As to the in vivo data only a few patches were compared to the ground truth. Similarly, the distance error was between 0.25 mm ± 0.17 mm and 0.42 mm ± 0.53mm. Due to inhomogeneous grey level intensities in the in vivo data, constant segmentation parameters and intensity based point filtering in the last segmentation processing stage some patches had a fragmented surface. An automatic parameter selection scheme should be able to remedy this. Two reconstructed surface patches of the bone phantom and the in vivo data, respectively, can be seen in figure 2.

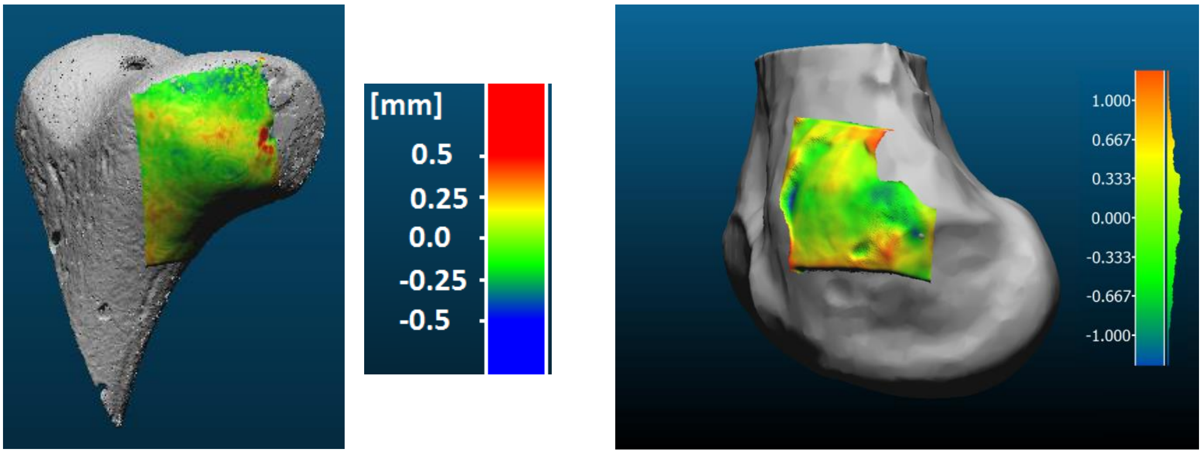

Figure 2: Examples for resulting patches for the bone phantom (left) and the human knee (right).

DISCUSSION

We developed an image processing protocol and algorithm to extract bone surfaces from 3D ultrasound volume images. Compared to ground truths obtained from CT and MRI, respectively, the segmentation accuracy was in the submillimeter range. In numerous areas, the deviation of the segmentation result from the reference geometry was even below the resolution of the reference geometries.

Since grey level intensities of bone structures in ultrasound images depend on the relative transducer orientation, entirely intensity based methods may be limited. Symmetry based approaches offer good alternatives. Especially in the case of bone surface responses which possess a ridge like (Jain2004) and thus symmetric intensity profile. Apart from potentially better segmentation accuracies the repeatability is improved as well.

The segmentation framework we proposed is primarily based on level set methods. The advantage of these methods is their implicit description of shape. In contrast to parametric approaches, topological changes are handled automatically. In addition, level set methods originate from a sound theoretic framework which easily allows for incorporating various constraints in the form of external energy terms what we made use of in the level set evolution.

In low contrast areas the curve evolution may be less controlled compared to the evolution in high contrast areas. This was specifically observed in the border areas of the bone surfaces. A statistical shape model approach (Cootes1995, Tsai2003) might help due to its specificity, i.e. due to a curve evolution only within statistical limits. However, for this a set of training data sets is needed to build up the model. Also, the acquired US images must be aligned properly.

Our work is based on that of (Hacihaliloglu2009) who developed a framework for bone fracture detection of straight structures. Since our work deals with arbitrarily formed shapes we had to adapt the approach accordingly. Instead of using the Radon transform to obtain the local orientation, in this work the structure tensor was used. In addition, we did not use the 3D phase symmetry filter response directly but incorporated it into a level set framework. As a result, we obtain a distinct surface which can be easily transformed into a mesh, for instance.

(Belaid2011) incorporated a feature asymmetry measure into a level set framework. The difference to our work is that they used Cauchy kernels instead of Log-Gabor filters to compute the asymmetry measure since these shall have better properties. Furthermore, their framework operates on 2D images only even though their methods might be extended to 3D.

A work related to the entire reconstruction of the femur was presented in (Barratt2008). The group instantiated a statistical shape model of the femur by using 3D ultrasound data. The average root-mean-square distance error between the reference surface and the reconstructed surface was 3.5 mm.

In our actual work we used segmented bone surface patches to reconstruct relevant parts of the knee joint based on registered image patches to obtain e.g. a distal femur bone model. Due to acoustic shadowing only part of the femur geometry could be scanned. After registration, an incomplete model was obtained and a statistical shape model was fitted. The average reconstruction error was less than 0.967 mm (see figure 3).

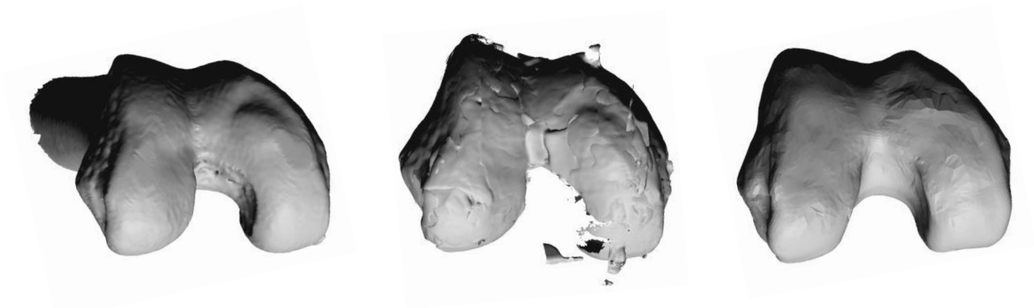

Figure 3: CT based reconstruction of a solid foam bone phantom (*SAWBONES*) of the distal femur (left), segmentation and registration result of surface patches from ultrasound volume images (middle), reconstruction result after fitting a statistical shape model (right).

Alternatively, morphing algorithms (cf. Amberg2007) can be used and have been evaluated. These aspects will be subject of another paper.

In conclusion, we developed a new method that allows for reconstructing relevant areas of the distal femur based on US image data with accuracies in the submillimeter range.

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