Scene-Based Segmentation of Multiple Muscles from MRI in MITK

Yan Geng[1], Sebastian Ullrich[2], Oliver Grottke[3], Rolf Rossaint[3], Torsten Kuhlen[2], Thomas M. Deserno[1]

[1]Department of Medical Informatics, RWTH Aachen University
[2]VR Group, RWTH Aachen University
[3]Department of Anaesthesia, University Hospital Aachen
ygeng@mi.rwth-aachen.de

Abstract. Segmentation of multiple muscles in magnetic resonance imaging (MRI) is challenging because of the similar intensities of the tissue. In this paper, a novel approach is presented applying a scene-based discrete deformable model (simplex mesh). 3D segmentation is performed on a set of structures rather than on a single object. Relevant structures are modeled in a two-stage hierarchy from groups of clustered muscles (as they usually appear in MRI) to individual muscles. Collision detection is involved during mesh deformation to provide additional information of neighboring structures. The method is implemented in C++ within the Medical Imaging Interaction Toolkit (MITK) framework. As a proof of concept, we tested the approach on five datasets of the pelvis, three of which have been segmented manually. Indicating the potential impact of the method, we do not claim its general validity yet.

1 Introduction

Magnetic resonance imaging (MRI) and magnetic resonance angiography (MRA) provide efficient and flexible means for medical diagnostics and research. Within the scope of the regional anaesthesia simulator (RASim) project[1]), a virtual reality-based simulation for performing local anesthetics on individual virtual patients is developed [1, 2]. The simulation requires accurate medical models of different tissues from human body, which are generated from MRI volume datasets.

So far, fuzzy c-means clustering was used to segment bone and muscles as well as vessels from MRI and MRA, respectively [3]. Each pixel is assigned to the nearest cluster whose value is close to the mean of this cluster. The problem here is the similar intensity on MRI and the pixels inside a structure always have the alike values as the pixels in the surrounding structures. Therefore, those pixels are assigned to one cluster and multiple muscles cannot be separated.

Yushkevich et al. proposed two well-known three-dimensional (3D) active contour segmentation methods: Geodesic Active Contour and Region Competition in the software application ITK-SNAP [4]. Both methods use the deformable

[1] http://www.rasim.info

model based on a feature image of edges or intensity regions by computing internal and external forces. However, the external force is derived either from the gradient magnitude or by estimating the probability that a voxel belongs to the region of interest vs. the background, which is unsuitable in MRI data.

Jurcak et al. proposed an atlas-based segmentation for the quadratus lumborum muscle [5]. Atlas-based segmentation is a powerful tool for medical image segmentation when a standard atlas or template is available. Then, segmentation can be treated as a registration problem. Due to the variability in morphology and shape of human tissue and organs, respectively, it is challenging to create an atlas or even an atlas database for individual muscles.

Model-based segmentation with deformable simplex meshes have been introduced to MRI by Delingette [6] and improved by Gilles et al. for multiple objects [7]. Thanks to the simple geometry definition of simplex meshes, they have been proved to be efficient particularly in terms of flexibility and computational cost.

In this paper, we extend this approach to scene-based segmentation of individual muscles in MRI and model a two-stage scene hierarchy to improve both, speed and quality.

2 Materials and Methods

2.1 Simplex Mesh

A k-simplex mesh is considered as a $(k + 1)$-connected mesh: each vertex has exactly $(k+1)$ distinct neighboring vertices. This simple geometry feature yields efficient calculation of the deformation. In this paper, we use 2-simplex meshes for the deformable model, which can be generated directly from manually labeled image as reference data. The internal force is controlled by tangential and normal components based on the geometry of the simplex mesh to keep the shape smoothing during the deformation. The calculation of the external force is also based on the gradient of the input image. The vertices are driven by the external force and move to the voxels of maximum gradient intensity on their normal lines.

Therefore, the problem caused by similar intensities both on the input MRI data and its gradients still affects the result of deformation like other deformable models, namely, the gradients can't provide enough edge information for a single deformable model. Hence, a scene-based collision detection is applied introducing additional forces when segments are about to get in contact during the iteration. Considering two neighboring simplex meshes in 3D space that are not separated by a clearly defined edge, they will balance each other on a reasonable location.

In other words, low contrast in parts of MRI is compensated by internal and scene-based 3D a-priori information.

2.2 Collision Detection

The collision detection is achieved from bounding volume hierarchies (BHV) [8]. We choose the axis-aligned bounding box (AABB) as bounding volume of simplex mesh and subdivide it recursively to fill up the children nodes in the octree (a commonly used partition of 3D space by recursively subdividing in eight octants) until a user defined threshold is reached. The hierarchical traversal scheme is applied for collision detection (Fig. 1). If two leaf nodes collide and their intersection contains the vertices from the corresponding meshes, the collision response acting like a compressed spring is contrary. The non-collision state is stored for each vertex in every iteration.

Fig. 1. Hierarchical traversal scheme for bounding volumes A and B.

```
Traverse(A,B)
if A and B do not overlap then
   return
end if
if A and B are leaves then
   return intersections of primitives enclosed in A and B
else
   for all children in A[i] and B[i] do
      traverse(A[i],B[i])
   end for
end if
```

2.3 Hierarchy

Beside the general coarse to fine scheme of mesh-based segmentation, we implemented an additional two-stage object hierarchy. In the first stage, segmentation of muscle groups, vessels and bone is performed. The second stage divides each muscle group into the individual muscles it is composed of (Fig. 2).

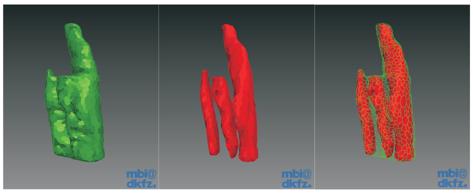

Fig. 2. Two-stage hierarchy in modeling muscles: (a) cluster of muscles; (b) individual muscles; (c) superimposition. The pelvis region models the adductor muscles containing the add. brevis, add. longus, and add. magnus.

During the segmentation, deformation begins with the simplex meshes of the groups until convergence is reached. Then, the displacements of the individual muscles inside the groups are determined. The final positions provide accurate edge information for all structures, and the number of iterations is reduced. Also, the steps of collision detection are reduced yielding remarkable performance gain. For instance, modeling two muscle groups with more than 30,000 vertices an iteration incl. collision detection takes less than 5 s.

2.4 Implementation

Implementation in C++ relies on the Insight Toolkit (ITK), the Visualization Toolkit (VTK) and the Medical Imaging Interaction Toolkit (MITK) frameworks. At first, the ITK standard 3D registration of target to reference dataset is performed. Scene-based segmentation is initialized with a mean model computed by co-registration of all three references. Using mutual information, the transform matrix is computed on MRI but then applied to the labeled data.

3 Results

The algorithm is tested on datasets of the pelvis region. Reference data is composed of co-registered MRI and MRA examinations from five subjects, selected to span a large variance in body mass, height, age, and gender. Three datasets have been segmented manually by experienced anatomists. They are used as reference models. In total, 25 muscles have been labeled (Fig. 3, Fig. 4). A complete automatic segmentation with two muscle groups (subdivided into 12 individual muscles) and bone takes about 15 min.

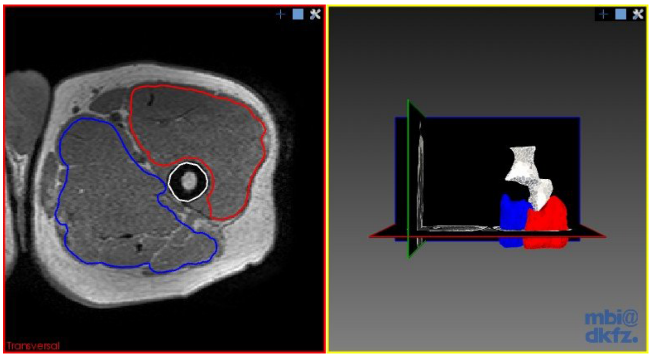

Fig. 3. Segmentation result on the top level (cluster of muscles).

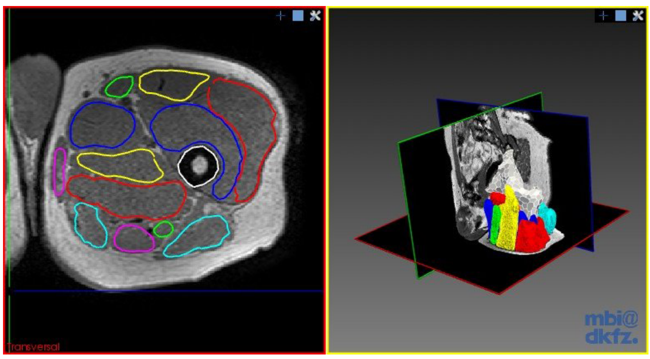

Fig. 4. Segmentation result on bottom level (individual muscles).

4 Discussion

Combining deformable simplex mesh and collision detection in 3D provides an efficient method for scene-based segmentation for multiple muscles from MRI. The presented approach contributes a scene-based mesh segmentation that is capable to extract/match individual muscles, which have fairly poor contrast in the source data. The proof-of-concept scene is composed of about 25 objects, which are divided into sub-scenes of at most eight objects using a two-stage hierarchy. This has remarkable performance gain in both, computation time and quality. Collision detection gives the deformable models additionally the missing edge information where no clearly defined boundary is available.

The first visual results are promising and more experiments are planned to assess the precision quantitatively. Using only two references to initialize the algorithm, error measures become computable in a leaving-one-out design. Highest precision is not the goal of this approach. However, plausible approximated results are sufficient for most training simulators. Furthermore, adaption to other body regions with even more complex structures is planned.

Aknowledgements

This work was developed under the auspices of the German Research Foundation (DFG, RO 2000/7-1, KU 1132/4-1, LE 1108/8-1).

References

1. Ullrich S, Grottke O, Fried E, et al. An intersubject variable regional anaesthesia simulator with a virtual patient architecture. Int J Comp Ass Radiol Surg. 2009;4(6):561–570.
2. Grottke O, Ntouba A, Ullrich S, et al. Virtual reality-based simulator for training in regional anaesthesia. Br J Anaesth. 2009;103(4):594–600.
3. Teich C, Liao W, Ullrich S, et al. MITK-based segmentation of co-registered MRI for subject-related regional anaesthesia simulation. Procs SPIE. 2008;6918:2M1–2M10.
4. Yushkevich PA, Piven J, Hazlett HC, et al. User-guided 3D active contour segmentation of anatomical structures: Significantly improved efficiency and reliability. NeuroImage. 2006;31(3):1116 – 1128.
5. Jurcak V, Fripp J, Engstrom C, et al. Automated segmentation of the quadratus lumborum muscle from magnetic resonance images using a hybrid atlas based - geodesic active contour scheme. In: Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE; 2008. p. 867–870.
6. Delingette H. General object reconstruction based on simplex meshes. Int J Computer Vis. 1999 Sep;32(2):111–146.
7. Gilles B, Moccozet L, Magnenat-Thalmann N. Anatomical modeling of the musculoskeletal system from MRI. Proc MICCAI. 2006; p. 289–296.
8. Ericson C. Real-Time Collision Detection. Morgan Kaufmann; 2004.