

3D Visual Presentation of Shoulder Joint Motion

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Abstract

The 3D visual presentation of biodynamic events of human joints is a challenging task. Although the 3D reconstruction of high contrast structures from CT data has been widely explored, then there is much less experience in reconstructing the small low contrast soft tissue structures from inhomogeneous and sometimes noisy MR data. Further, there are no algorithms for tracking the motion of moving anatomic structures through MR data. We represent a comprehensive approach to 3D musculoskeletal imagery that addresses these challenges. Specific imaging protocols, segmentation algorithms and rendering techniques are developed and applied to render complex 3D musculoskeletal systems for their 4D visual presentation. Applications of our approach include analysis of rotational motion of the shoulder, the knee flexion, and other complex musculoskeletal motions, and the development of interactive virtual human joints.

1. Introduction

Evaluation of the motion pattern of joints and soft tissues in the living human being is difficult. Understanding of motion pattern and the biodynamic events of supporting soft tissues structures of joints would be important in determining the reasons for the development of various joint disorders. The lack of means to noninvasively evaluate the 3D motion pattern in vivo has been hindering the development of methods to prevent and reliably treat these disorders. The shoulder joint is one of the most complex joints in the human body. Since the evaluation of its motion pattern during complex tasks is very important for the understanding of the above mentioned reasons in the living person; it is important to develop high resolution 3D in vivo techniques to evaluate them.

MRI has been shown to be an ideal imaging modality due to its soft tissue characterization capability for evaluation of soft tissue and bone structures of the musculoskeletal system. This technology provides, besides exquisite spatial resolution, also volumetric data for 3D tissue analysis. Although the 3D reconstruction of high contrast anatomical structures from CT data has been widely used, 3D volume rendering of complex soft tissue structures from MR data, due to its complexity, is much less explored[1]. The reasons for difficulties are the low contrast resolution, gross inhomogeneities of receiver coils, and to a certain extent the detailed infrastructural information.

Image segmentation is the standard technique used to differentiate anatomical structures in high contrast images. However, so far there are no unsupervised algorithms available to reliably segment all the soft tissue components of musculoskeletal system and bones. Also,

there is no unsupervised algorithm to segment the soft tissue structures of the moving joints for their 3D/4D visual presentation and virtual manipulation.

The anatomical structures of the analyzed joints, including tendons, cartilage and even muscles are relatively small. Their visualization requires a use of special receiver surface coils, which induce field inhomogeneity and shading into the acquired data. This shading and inhomogeneity causes problems in the tissue segmentation. Another problem is caused by the properties of the soft tissue structures themselves, especially by the tendons and cartilage. Several 3D segmentation algorithms have been proposed for volumetric medical images[2][3][4][5][6][7]. However, most of them are supervised and rely on the expert knowledge of the operator.[3],[4] The supervision limits their range of applications to some specific anatomical structures and organs which have relatively simple shapes, including bones, hearts, hippocampi, kidneys, etc. The supervised technique could be applied to more complex structures; however, that is not practical. The unsupervised segmentation techniques as they exist are limited in the range of structures they can segment and imaging modality they can handle[2][5]. Other successful techniques are based on the creation of anatomical atlases. In theory, once an anatomical atlas has been created, it can be deformed or warped to match the image to be segmented [6],[7]. The main drawback of this method is its inability to handle abnormal human anatomy. The region growing based segmentation algorithm could, at least in theory, be most useful for this task[8]. However, just a few of them have in the past been applied to the segmentation of 3D structures. To eliminate that drawback, we developed our own 3D segmentation algorithm based on the accurate estimation of local statistical properties of the tissues. To handle the data acquired during a motion, we developed an accurate motion tracking algorithm which is used to pass the segmentation from volume to the next.

2. Purpose

The purpose of this study was to develop a spatially adaptive and time adaptive 3D segmentation algorithm and 4D display of the motion of soft tissue structures and bones of the joints using 3D GRE MRI data and apply that method for the analysis of a series of MRI volumes which were acquired during shoulder motion.

3. Methods

For the acquisition of the 3D volumetric data two female volunteers, aged 21 and 23 years were imaged using chemical shift GRE imaging sequence with optimized imaging parameters. The right shoulders of both volunteers were imaged first in neutral position then when they rotated their right arm stepwise from neutral position to the maximal external rotation. A total of eight series of images were acquired on both volunteers.

3.1 Segmentation

The first image on the series is segmented using a region growing algorithm which basically performs the segmentation via the estimation of the connectivity between neighboring voxels. Although there are many ways to estimate the connectivity, the best approach requires an accurate estimation of the mean and variance of every voxel neighborhood. Figure 1 shows our 6 local neighbors as well as the possible connectivity based on the voxel statistics. Using these statistics, the connectivity between voxels can be established. The problem resides in that the mean and variance are related to the sum of the locally connected voxel values and to the sum of the square values of the same locally connected voxels, and this connectivity information is what we are trying to estimate.

To overcome the circular problem, we have to propose a set of hypotheses regarding the possible connectivity between voxels. Our main hypothesis is based on the assumption that

there are only three possible local orthogonal edge processes on every voxel in the image. These edge processes are shown in Figure 2 .

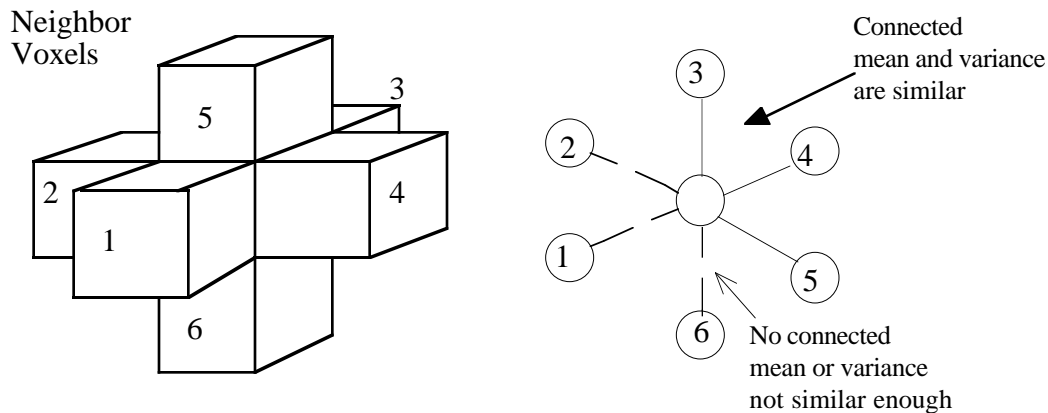


Figure 1. 3D six neighbor system, and graph representation

By constraining the edge processes to only three orthogonal edge processes we reduce our search space to six local connected neighborhood systems, as seen in Figure 2b. Refinements including lines and diagonals are also possible.

Having only six possible connected neighbors allows us the estimation of six possible means and variances for every voxel in the image, and now the problem is to define which one is the best, which is not trivial. To simplify our problem further, we decided to apply a different approach. Instead of estimating six possible means and six possible variances, we propose the use of a standard image restoration technique for the estimation of the voxel group mean value[9]. ; This reduces our problem to an estimation of the variance which now is equivalent to find the neighborhood that provides the minimum variance. Once we have estimated the variance and the neighborhood system to whom it belongs the connectivity is estimated by performing an *f*-test to the other estimated variances and looking for those that are similar[10]. If they are similar then these neighborhood systems are connected. In that way we estimate the connectivity of every voxel in the image.

Once the inter voxel connectivity has been estimated the segmented image is just a set of all the independent regions whose voxels are connected to each other. Although the segmentation based on the connectivity is fairly good it has to be refined on the regions boundaries due our edge process assumption. Furthermore, certain complex anatomical structures do not follow our model, thus they are going to be miss-segmented or broken into many independent patches. To address the boundary problem we used a standard relaxation labeling approach based on a Gibbs random field model of the image segments [11]. The broken region problem is solved by using a region merging algorithm based on a standard *t* test between local region means. These two additional steps allow us to get a detailed segmented volume, which will be used to generate our 3D surfaces and by our motion tracking algorithm.

3.2 Motion tracking

Once we have segmented the first volume image, we can label each region and assign general material properties to each one of the segmented anatomical structures like relative elasticity, color, etc. Now, the segmentation of the next volume in the sequence can be done by applying the same segmentation algorithm, but there are certain problems in using this approach. First, the boundary between low contrast structures is not well defined, thus although we are applying the same algorithms, noise causes the boundaries found by the segmentation to change between series. The second problem resides in the region labeling of the image. There are so many structures that labeling them consistently at each volume in the

sequence is not trivial. Third, the segmentation algorithm is very demanding computationally, thus segmenting each volume using this process is also impractical. Given these three objections we decided to use an alternative approach for the segmentation of the remaining volumes in the series.

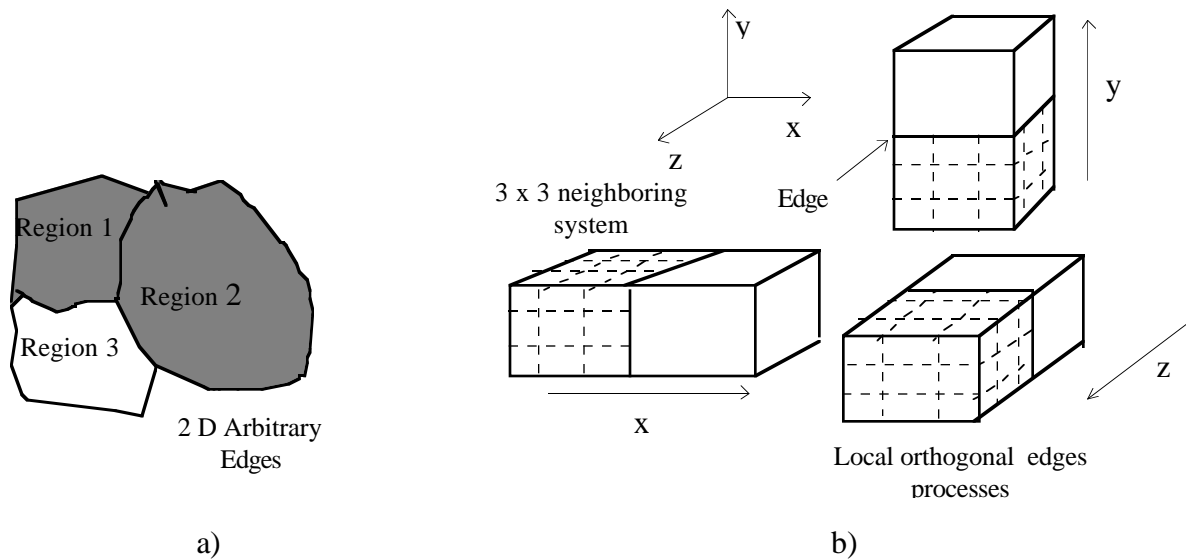


Figure 2. Arbitrary edges and 3D local orthogonal edge processes in a 3x3x3 neighboring systems

The motion estimation and tracking will give us information needed to pass the segmented image from one frame to the other[12]. Now, the problem is that shoulder motion has a rigid and non-rigid components that has to be taken into account when performing the estimation of 3D motion. Our algorithm estimates the motion vector of each voxel after the registration of the edges at two consecutive images which are extracted from the raw data using a Canny edge detector[13]. The registration takes into account the local deformations of soft tissues by using a priori knowledge of the material properties of the different structures found at the segmentation step. Also, this knowledge allows us to apply two different strategies. One for recovering the rigid motion of bones and the other for the soft tissues.

Once the edges have been registered, the motion vectors of every voxel in the image are computed by interpolating the motion of the edge points. This interpolation uses only the point that belongs to the same anatomical structure and the material elasticity properties. After the estimation of the motion vector for each voxel the segmentation of the second volume is just the application of motion vector to the segmented data of the former volume. This process is repeated until all the volumes in the sequence are segmented.

3.3. 3D/4D visualization

Once we have segmented the whole set of images, textured surfaces of each one of the major structures including fat, muscles, bone, tendons, and cartilage were computed[14]. The textured surfaces reflected the major attachments of the tendons in the humeral head. Furthermore, the Canny edge detection algorithm was used separately to detect all the edges which were present in the volume data, that approach rendered the major interfaces including fascial planes and tendons within the musculoskeletal structures.

Figure 3 shows a flow chart of the method used to segment and visualize all the major components of the shoulder.

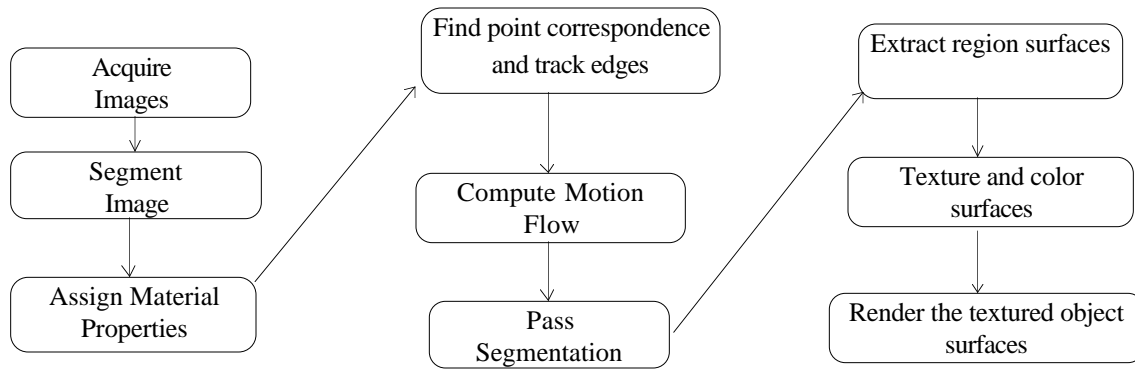


Figure 3. Flow Chart

4. RESULTS

We ran our segmentation algorithm on two sets of MRI data, and we used Iris Explorer to visualize our extracted surfaces. Image 4 a) shows three orthogonal planes from one of them. The segmentation algorithm successfully labeled the major components of the shoulder like the humeral head, muscle, fat, etc. Figure 4 b) shows the surface rendering of the humeral head that has been textured according the values of the raw data that touch its external surface. While the muscle tissue is shown in figure 5 a). This figure shows a composite rendering of the muscle tissue and the humeral head. As we know, segmentation of the 3D data provides a lot of flexibility in the visualization and manipulation of the individual components. Figure 5 b) shows the process of the virtual extraction of the humeral head form the shoulder. Here the muscle tissue has some transparency that also enables to see the interior of the shoulder. Furthermore, this manipulation allows us to see the tissue that is attached to the humeral head.

Using our motion tracking algorithm the segmented data from the first volume was passed successfully to the rest of the volumes in the sequence. Figure 6. shows the complete upper arm rotation sequence made of 8 frames. Here the muscle tissue has a very high transparency to allow the visualization of the humeral head rotation. Also, this data was used to generate a movie of the moving shoulder which was displayed in our system and then copied to tape.

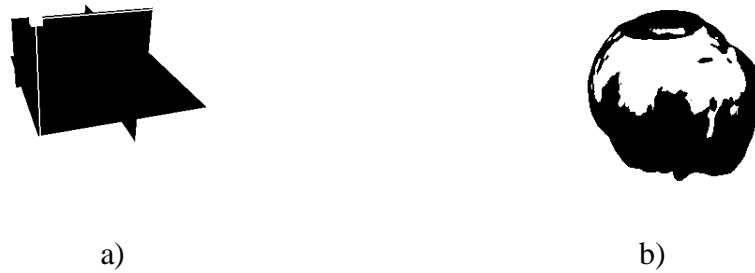


Figure 4. a) Three orthogonal Planes. b) Surface Rendering of the humeral head

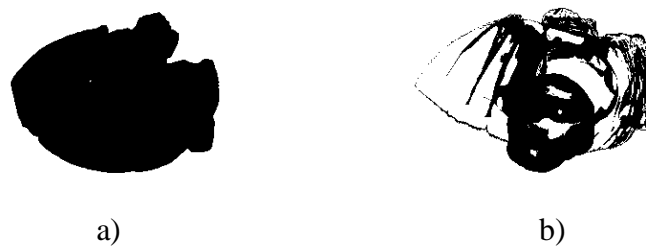


Figure 5. a) Muscle tissue and humeral head. b) Virtual Manipulation of the humeral head.

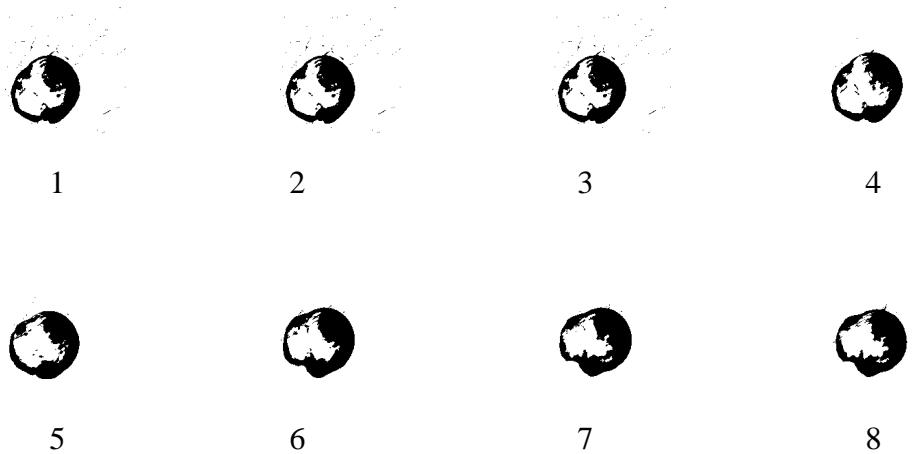


Figure 6. The eight frames of the rotating upper arm sequence.

The movie shows the rotation of the humeral head in different positions as well the motion of the tissues and the cartilage. We also included in the movie the motion of the edges extracted using the Canny edge operator that enable us to visualize the motion of the tendinous fascicles within the muscles.

4. Conclusion

We presented a hierarchical application of an automatic, region-based segmentation algorithm, motion estimation and tracking, surface rendering and virtual reality tools to the

analysis of biodynamics of the shoulder joint. The different soft tissue structures, including tendons, muscles, cartilage, fat and bone were separated from each other using the segmentation algorithm and tracked in the sequence. After that the segmented tissues were color coded and their texture surface was extracted. The Canny edge detection allowed demonstration of tendinous fascicles inside the muscles. However, the various muscles could not be completely separated from each other due to the fat suppression pulse sequence employed. A-priori knowledge of the tissue elasticity were used by the motion tracking algorithm to estimate the motion of different anatomical components present in the data.

The visualization of various anatomical components was done by rendering realistic surfaces of them using the segmented data. Furthermore, the 3D segmentation approach used allowed the display of the motion pattern of the humeral head in the glenoid as well as the motion of the tendons in an interactive environment.

6. Acknowledgment

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7. REFERENCES

- [1] U. Tiede, K. H. Hoehne, M. Bomans, A. Pommert, M. Riemer and G. Wiebecke, "Investigation of Medical 3D-Rendering Algorithms" *IEEE Computer Graphics and Applications* 10(2):41-52, March 1990
- [2] W. M. Wells III, W.E.L. Grimson, R. Kikins and F. A. Jolez, "Adaptive Segmentation of MRI Data". *IEEE transactions on Medical Imaging* pp. 429-440, 1996.
- [3] M.W. Hansen and W.E. Higgins "Relaxation Methods for Supervised Image Segmentation", PAMI-19 pp 949-962. 1997.
- [4] E. A. Ashton, K. J. Parker, M. J. Berg and C. W. Chen, "A novel Volumetric Feature Extraction Technique with Applications to MR Images", *IEEE transactions on medical Images* vol 16 no 4 pp 365-371, 1997.
- [5] J. Rajapalse, J. N. Giedd and J. L. Rapoport, "Statistical Approach to Segmentation of Single-Channel Cerebral MR Images", *IEEE Transactions on medical imaging*, Vol 16, No. 2, pp 176-186, 1997.
- [6] M. Gado MD. et al. "Three dimensional Hippocampal MR Morphometry with High-dimensional Transformation of a Neuroanatomical Atlas". *Radiology* 1997;202:504-510;
- [7] G. E. Christensen, R. D. Rabbitt, M. I. Miller, "3D brain mapping using a deformable neuroanatomy". *Physics in Med and Biol*, 39, pp.609-618, March 1994.
- [8] R. M. Haralik and L. Shapiro, "Image Segmentation Techniques", *Computer vision Graphics and Image Processing* pp 100-132, 1985.
- [9] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Addison-Wesley 1992.
- [10] D. C. Montgomery, *Design and Analysis of Experiments*, John Wiley & Sons, Inc. 1984.
- [11] S. Geman and D. Geman, "Stochastic relaxation, Gibbs distribution, and Bayesian restoration of images," *IEEE Transaction on. Pattern Analysis and Machine. Intelignce.* vol 6. pp 721-741 Nov 1984.
- [12] A. M. Tekalp, *Digital Video Processing*, Prentice Hall Signal Processing Series. 1995
- [13] J. Canny, "A computational Approach to Edge Detection", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol PAMI-8 (6):679-698. 1986
- [14] M. Levoy "Display of Surfaces from Volume Data" *IEEE Computer Graphics and Applications* 8(5):29-37, May 1988.