The Third Joint Workshop on
Machine Perception and Robotics
(MPR2007)

A Feature Tracking-based Approach for Local Deformation Fields Measurement of Biological Tissue from MR Volumes

Penglin Zhang*†, Shinichi Hirai* and Kazumi Endo*
*Ritsumeikan Univ. / Faculty of Science and Engineering, Kusatsu, Japan
†Wuhan Univ. / School of Remote Sensing and Information Engineering, Wuhan, China

Abstract— **While a variety of different deformable model algorithms have been reported for the deformation measurement of biological tissue, few attempts in feature tracking areas have been reported. In this paper, we investigated the feature point automatic extraction and tracking technique to measure local deformation fields from 3D MR volumetric images. To track the precisely homologous position in the deformed MR volumetric image for the given feature point in the initial MR volumetric image, a least squares-based 3D image matching method was introduced. To test the validity of our approach, we applied the proposed method to MR volumetric images of a volunteer's calf. Our preliminary experimental results indicate that the proposed approach is feasible .**

I. Introduction

Since its initial use for human imaging more than 20 years ago, magnetic resonance imaging (MRI) has become a widely used clinical imaging modality [1]. MRI is being increasingly employed in biomedical applications. Accordingly, MR image processing techniques have become a central issue in biomedical applications. However, most studies over the past decades focused on MR image segmentation, registration and reconstruction, with biological tissue deformation measurement and physical parameter estimation being performed in only a few studies.

With the increasing application of biomedical imaging, it is becoming more important for computer-assisted clinical diagnosis, surgery simulation and operation planning to acquire knowledge regarding the motion and deformation of biological tissue. Moreover, there is much focus on the physical characteristics of tissues. In the past decade, there has been much research involving deformation measurements from MR volumetric images using elastic deformable models [2] [3] [4]. In general, deformable models can be classified into two categories: parametric and geometric active models [5]. The parametric active contours, also called snakes, were first introduced by Kass, Witkin and Terzopoulos in 1987 [6]. They are widely used in deformation estimation, segmentation, motion tracking and registration of biomedical images. Later, many researchers expanded and developed their own approach based on it. Lang et al. [7], Cho et al. [3] and Matuszewski et al. [2] proposed estimating the deformation of the object based on the parametric active contours. Their general idea of parametric active contours is to first define an energy function in which the local minimum is obtained at the boundary of the object, and then to try to minimise the designed function to deform a given initial contour toward the boundary of the object to obtain the object's deformation.

The geometric active model was first proposed by Caselles et al. [8]. Malladi et al. [9], Caselles [10] and Chenoune et al. [5] developed different aspects of this method, but their geometric partial differential equations were proposed by Caselles et al. [8]. They used the propagation of curves and surfaces for boundary detection and motion tracking.

Although the deformable model algorithm has undergone significant development, some problems remain. The energy model of parametric active contours is not capable of handling changes in the topology of the evolving contours when direct implementations are performed, and special, often heuristic, topology handling procedures must be used [10]. The geometric active contours do not work well for objects that have poor contrast. That is, when the object boundary is indistinct or has gaps, the contours tend to leak through the boundary [11]. In addition, it is difficult to characterise the global shape of an object with the geometric active contour algorithm.

To avoid the problems associated with the deformable model algorithm, we propose a feature tracking-based approach to measure local deformation of biological tissues or organs from biomedical MR volumetric images. In our method, we first automatically extract the high curvature feature points (also called points of interest) in the initial MR volumetric image, and then use the proposed tracking approach to track the corresponding positions in the deformed MR volumetric image. The local deformation field is computed depending on corresponding feature point pairs.

This paper is organised as follows. Section 2 outlines our approach. Section 3 introduces the approach for feature tracking and 3D deformation fields measurement. Section 4 presents examples and the results of preliminary experiments. The final section presents our discussion and conclusions.

II. Overview

The process of our approach can be summarised as shown in Figure 1.

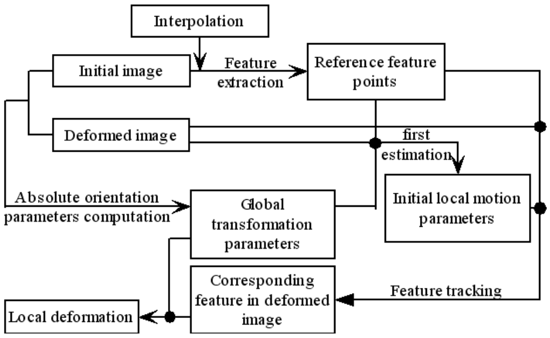

Fig. 1. overview of our approach.

The proposed method consists mainly of feature extraction, computation of absolute orientation parameters and feature tracking. The purpose of feature extraction is to allow the automatic extraction of 3D points of interest from the initial MR volumetric images as references for feature tracking. Our approach is an extension of the Harris operator [12] to three dimensions. Therefore, we obtain an auto-correlation matrix of the 3D Harris operator given by

$$\mathbf{M} = \mathbf{G} \otimes \begin{pmatrix} I_x^2 & I_x I_y & I_x I_z \\ I_x I_y & I_y^2 & I_y I_z \\ I_x I_z & I_y I_z & I_z^2 \end{pmatrix}$$

where I_x, I_y and I_z are computed by convolving the image with a gradient template along the $x-$, $y-$ and $z-$axes. The Gaussian template $\mathbf{G}$ reduces the influence of noise.

The eigenvectors λ_1, λ_2 and λ_3 of the matrix $\mathbf{M}$ are the three principle curvatures. Let the points of interest be those points where the value of the response function is above a given threshold. According to the original idea of Harris, a response function is defined as:

$$R_F = \frac{det(\mathbf{M})}{trace(\mathbf{M})}$$

where $det(\mathbf{M})$ and $trace(\mathbf{M})$ are the determinant and trace of the matrix $\mathbf{M}$, respectively. We use this extended Harris operator to detect the 3D points of interest from the MR volumetric image.

In the absolute orientation process, we find the relationship between two coordinate systems in the two MR volumetric images. The critical problem of absolute orientation is to find the solution of the transformation parameters, which include the rotation matrix $\mathbf{R}$ and translation vector $\mathbf{T}$. In this case, we select some feature points around the bone, which can be regarded as rigid, and use the unit quaternion proposed by Horn [13] to solve the transformation parameters. The transformation parameters thus obtained are used to transform the initial (or deformed) coordinate systems with respect to the deformed (or initial) systems. In this way, we can compute the deformation under a uniform coordinate system.

We note that the the resolution along z-axis usually is lower than x- and y-axis. Therefore, to ensure that there is sufficient resolution along the z-axis, we use linear interpolation to increase z-resolution before feature extraction and matching. As a result, we obtained two discrete voxel-based 3D MR volumetric images (initial and deformed), the resolutions of which along the $x-$, $y-$ and $z-$axis are similar or even identical.

III. Feature Tracking and Deformation Fields Measurement

For a feature point $\mathbf{p}$ in the initial MR volume, to track the final location of its homologous point $\mathbf{p}'$ in the deformed MR volume, we first select a cubic region $\mathcal{C}_m$ (match cube) around $\mathbf{p}$ as the *template*. Then, to search its conjugate region $\mathcal{C}'_m$ in the deformed MR volume. After obtaining the $\mathcal{C}'_m$, its center usually be regarded as the location of $\mathbf{p}'$.

In this paper, we use Least Squares-based image matching algorithm proposed by Gruen and Akca [14] to search the conjugate regions.

A. Basic Least Squares Model

Given two discrete representative MR volumetric images sampled from the same part of a volunteer's calf under two different cases (initial and deformed). Let $\mathbf{x} = [x, y, z]^{\mathbf{T}}$ be the coordinate, $f(\mathbf{x})$ and $g(\mathbf{x})$ be the conjugate regions in the initial and deformed MR volumetric images respectively. If we assume that $f(\mathbf{x})$ represents a discrete cubic region around one feature point in the initial MR volume and regards it as *template*, then, $g(\mathbf{x})$ can be regarded as *search* region. Now, the problem becomes to obtain the final location and orientation of $g(\mathbf{x})$.

In an ideal situation, we should have.

$$f(\mathbf{x}) = g(\mathbf{x}) \tag{1}$$

Let $e(\mathbf{x})$ be the true error vector, then, taking the noise into consideration, we have a nonlinear observation equation:

$$f(\mathbf{x}) - e(\mathbf{x}) = g(\mathbf{x}) \tag{2}$$

In this way, the matching can be achieved by least squares minimization of a cost function, which represents the sum of squares of the residual between two regions.

To express the geometric relationship and deformed relationship between two conjugate regions, a 3D transformation taking account of geometric and deformed relationship is defined as:

$$\mathbf{x} = \mathcal{R}\mathbf{x}_0 + \mathcal{T} \tag{3}$$

where $\mathcal{T} = [t_x \ t_y \ t_z]^{\mathbf{T}}$ represents translation vector. $\mathbf{x}_0 = [x_0 \ y_0 \ z_0]^{\mathbf{T}}$ is the initial location of the conjugate region $g(\mathbf{x})$. And that parameterized rotation matrix $\mathcal{R}$ is described as:

$$\mathcal{R} = \begin{pmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ a_{20} & a_{21} & a_{22} \end{pmatrix}. \tag{4}$$

Linearization the right side of Eq.(2) by 1st order Taylor expansion yields

$$f(\mathbf{x}) - e(\mathbf{x}) = g^0(\mathbf{x}) + \frac{\partial g^0(\mathbf{x})}{\partial \mathbf{x}} d\mathbf{x} \tag{5}$$

where $g^0(\mathbf{x})$ is the initial position of $g(\mathbf{x})$. Furthermore, differentiation of Eq.(3) results

$$d\mathbf{x} = \mathbf{x}_0 d\mathcal{R} + d\mathcal{T} \quad (6)$$

with

$$d\mathcal{T} = \{dt_x,\ dt_y,\ dt_z\}, \quad (7)$$

$$d\mathcal{R} = \{da_{ij}\}, i,j = 0,1,2. \quad (8)$$

Using the notation

$$g_x = \frac{\partial g^0(\mathbf{x})}{\partial \mathbf{x}}$$

and substituting Eq.(6), Eq.(5) yield:

$$(f(\mathbf{x}) - g^0(\mathbf{x})) - e(\mathbf{x}) = \mathbf{x}_0 g_x d\mathcal{R} + g_x d\mathcal{T} \quad (9)$$

Rewriting above equation in matrix form, we have

$$-e = \mathbf{Au} - l \quad (10)$$

where $l = f(\mathbf{x}) - g^0(\mathbf{x})$, parameter vector $\mathbf{u}$ collects the parameters included in Eq. (7) and (8), and that coefficients in Eq. (9) are collected in matrix $\mathbf{A}$. Namely,

$$\mathbf{u}^\mathbf{T} = [dt_x,\ dt_y,\ dt_z, da_{ij}] \quad i,j = 0,1,2$$

$$\mathbf{A} = [\mathbf{g}_x\ x\mathbf{g}_x\ y\mathbf{g}_x\ z\mathbf{g}_x\ \mathbf{g}_y\ x\mathbf{g}_y\ y\mathbf{g}_y\ z\mathbf{g}_y\ \mathbf{g}_z\ x\mathbf{g}_z\ y\mathbf{g}_z\ z\mathbf{g}_z]$$

According to the literature [14], we know the residual v can be described as:

$$v = \mathbf{A}\hat{\mathbf{u}} - l \quad (11)$$

where $\hat{\mathbf{u}}$ is the estimation of $\mathbf{u}$.

The rest problem is to establish error equation voxel-by-voxel between $f(\mathbf{x})$ and $g(\mathbf{x})$ according to Eq.(11), and to obtain the least squares estimation $\hat{\mathbf{u}}$ through minimizing the sum of squares of residuals.

B. Application in Feature Tracking

So far, we have already established the least squares model for feature tracking. Now the problem situation becomes how to use the model. Since the nonlinearity of system (2), the final solution is obtained iteratively with the first approximations:

$$\mathcal{R}_i^0 = \mathbf{R}, \quad \mathcal{T}_i^0 = \mathbf{T} + \mathcal{D}_i^0, \quad (12)$$

where $\mathcal{R}_i^0$ and $\mathcal{T}_i^0$ represent the initial value of rotation matrix and translation vector, $i = 0,1,2,\cdots,n$ is the numbers of feature points. $\mathcal{D}_i^0$ represents the initial deformation vector of the i-th feature point, it is given by

$$\mathcal{D}_i^0 = \frac{(\mathbf{x}_i - \mathbf{x}_c)\mathbf{d}_{max}}{\mathbf{max}_{i=1}^n(\mathbf{x}_i - \mathbf{x}_c)} \quad (13)$$

where $\mathbf{x}_i$ and $\mathbf{x}_c$ are the coordinate of the i-th feature point and geometric center of the object, $\mathbf{d}_{max}$ is the maximum deformation of object, which is a prior constant.

After application of these first approximations, *1)* we obtains the *template's* initial location $g^0(\mathbf{x})$ in the deformed volume. Next, *2)* the correlation score (*cs*) between *template* and its corresponding region is computed. *3)* The iteration stops if the *cs* begin to decrease or exceed the given threshold. Or else, *4)* to obtain the solution vector $\hat{\mathbf{u}}$ using the least squares model mentioned above. After solution vector $\hat{\mathbf{u}}$ is obtained, it is used to update the transformation parameters in $\mathcal{R}$ and $\mathcal{T}$. *5)* The updated transformation in Eq. (3) is applied and $g^0(\mathbf{x})$ is resampled over the new set of coordinates. *6)* Go to the step *2)*.

C. Deformation Calculation

Let $\mathcal{D}_i = [dx,\ dy,\ dz]^\mathbf{T}$ be the displacement vector corresponding to the i-th voxel before and after deformation, $\mathbf{x}_1 = [x_1,\ y_1,\ z_1]^\mathbf{T}$ and $\mathbf{x}_2 = [x_2,\ y_2,\ z_2]^\mathbf{T}$ be the coordinate of the voxel in the initial and deformed MR volumetric image, respectively. Then, the displacement vector within global coordinate system is given by

$$\mathcal{D}_i = Tran(\mathbf{x}_1; \mathbf{R}, \mathbf{T}) - \mathbf{x}_2 \quad (14)$$

where $Tran(\mathbf{x}_1; \mathbf{R}, \mathbf{T})$ represents performing transformation $\mathbf{R}$ and $\mathbf{T}$ on $\mathbf{x}_1$.

IV. Experiment Results

In this section, practical examples were designed to demonstrate the capabilities of the proposed approach. All experiments were carried out using our own software developed using Visual C++, which runs on Microsoft Windows XP. All experimental results described below were obtained on a Dell PC with a 2.80 GHz Intel Pentium D CPU and 1 GB of RAM.

In experiments, all MR volumetric images were sampled from a volunteer's calf using an MR device under two different cases (initial and deformed). Both the initial and deformed MR volume (Fig.2) sets with FOV 20×20 cm and slice gap of 2 mm. In this case, linear interpolation algorithm was used to increase the resolution along z-axis. We thus obtained two sets of MR volumetric images with size of $256 \times 256 \times 37$, respectively. See Figure 3.

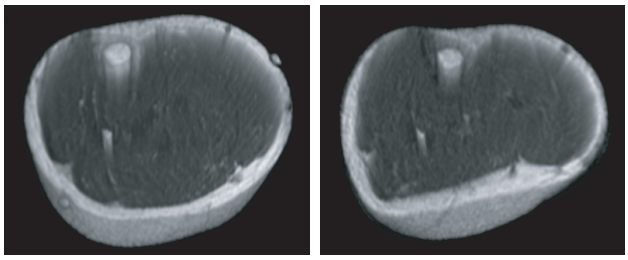

Fig. 2. MR volumes in the experiment (left: initial volume, right: deformed volume).

To test the validity of the proposed approach, we applied the proposed least squares-based feature matching approach(LSM-FM) to the 3D MR volumes shown in Figure 2. Moreover, to evaluate the feasibility of the proposed approach, the robust feature matching (RFM) approach proposed by [15] was applied to the same volumes. In the experiment, first, we performed the feature extraction algorithm described in the overview section on the initial volume to extract 500 feature points as reference points in feature matching. Whereafter, two approaches were

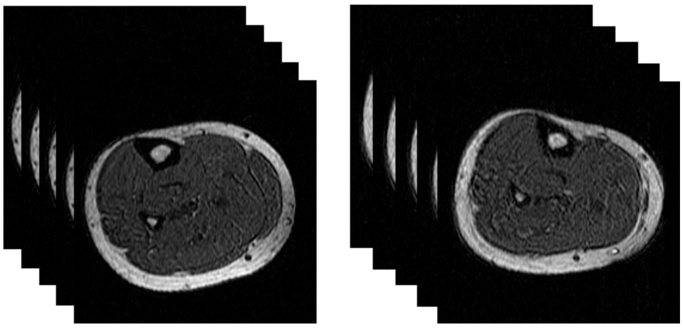

Fig. 3. MR volumetric images in the experiment (left: initial, right: deformed).

used to obtain the potential matches of reference points. Figure 4 shows the experiment results. For convenience to observe the deformation trend of the experiment data, we present the result of single initial slice overlaid on the deformed slice under a global absolute coordinate system. In the top row of Figure 4, the red contour illustrates the edge of deformed human calf and the blue one illustrates the edge of the initial one, respectively. In the down row of Figure 4, the left one illustrates the 3D local deformation fields obtained using RFM approach, and the right one illustrates the 3D local deformation fields obtained using LSM-FM approach.

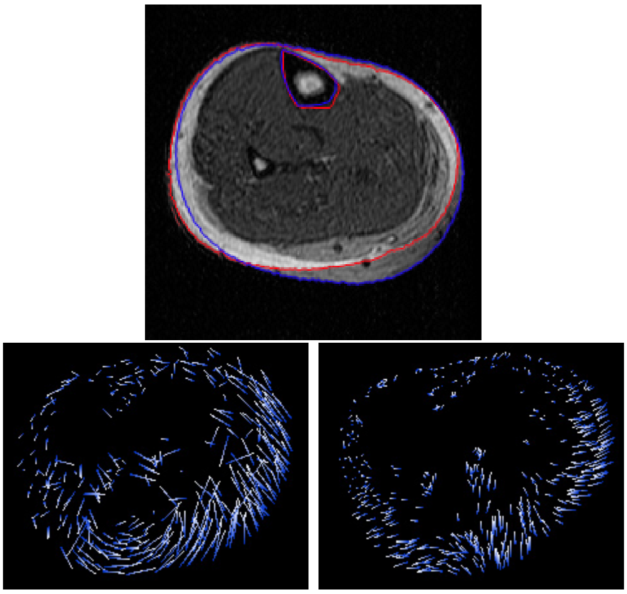

Fig. 4. 3D local deformation fields (Top:Deformed single slice overlaid on the initial slice,Left: RMS, Right: LMS-FM).

It is worth pointing out is: the result shown in Figure 4 was obtained with the size of *template* is $9 \times 9 \times 3$ voxels. It costed about 120 seconds.

Next, we use these two sets of matches obtained above as the input of the thin plate splines algorithm to compute the deformation fields, respectively. Whereafter, the computed deformation fields were used to deform the initial volume and result two computed deformation volumes. Finally, we use root mean squared (RMS) of residual differences (Eq. (15)) between computed deformation volume and actually deformed volume to reveal the validity of the proposed method.

$$\mathbf{E_{RMS}} = \sqrt{\frac{1}{N}\sum_{\mathbf{x}\in\Omega}(I_a(\mathbf{x}) - I_r(\mathbf{x}))^2} \qquad (15)$$

The result is: $\mathbf{E_{RMS}}(\mathbf{RFM}) = 58.445175$ and $\mathbf{E_{RMS}}(\mathbf{LSM-FM}) = 58.244834$, where $\mathbf{E_{RMS}}(\mathbf{RFM})$ is the computed RMS using the deformation fields obtained by RMS approach, $\mathbf{E_{RMS}}(\mathbf{LSM-FM})$ is the computed RMS using deformation fields obtained by LSM-FM approach. From this result, we note that the RMS of the proposed approach is smaller than the RMS, it reveals that the computed volume obtained using our approach is more similar to the actually deformed volume than it obtained using RMS approach. This result illustrates that our approach is feasible.

V. Discussions and Conclusions

The least squares method is a typically optimal algorithm. It has been widely used in a lot of fields. Image matching is one of its main applications (eg. [16], [17], [14],ect.). In this paper, we applied least squares method to the feature matching of 3D nonrigid and non-uniform object. Its advantages include:

1). The transformations in least squares model are modified constantly, thus, it is very suitable for non-rigid non-uniform object which transformations in different regions are different.

2). Comparison with deformable models which used in the deformation measurement, the featuring matching-based approach can measure the deformation not only the contour of object, but also the interior of object.

3). The feature matching based approach for deformation measurement doesn't need the initial contour of object, thus, it is independent of the shape of initial contour.

However, limitations still exist in the proposed approach:

1). The initial transformations need to be specified before using least squares model to carry out feature matching. And that the reliability of the initial transformations will affect the final matching result.

2). The false matches still appear in the match result. In order to improve the reliability and accuracy, the good ideas need to be proposed for removing the false matches.

References

[1] S. J. Riederer, "Current technical development of magnetic resonance imaging," *ENGINEERING IN MEDICINE AND BIOLOGY. IEEE.*, vol. 19, no. 5, pp. 34–41, 2000.

[2] B. J. Matuszewski, J. K. Shen, and L. K. Shark, "Estimation of internal body deformations using an elastic registration technique," *Proceedings of the International Conference on Medical Information Visualisation-BioMedical Visualisation*, pp. 15–20, 2006.

[3] J. Cho and P. J. Benkeser, "Elastically deformable model-based motion-tracking of left ventricle," *Proceedings of the 26th Annual International Conference of the IEEE EMBS*, vol. 1, no. 3, pp. 1925–1928, 2004.

[4] X. Papademetris, A. J. Sinusas, D. P. Dione, R. T. Constable, and J. S. Duncan, "Estimation of 3-d left ventricular deformation from medical images using biomechanical models," *Transactions on Medical Imaging. IEEE*, vol. 21, no. 7, pp. 786– 800, July 2002.

[5] Y. Chenoune, E. Delechelle, E. Petit, T. Goissen, J. Garot, and A. Rahmouni, "Segmentation of cardiac cine-mr images and myocardial deformation assessment using level set methods," *Computerized Medical Imaging and Graphics*, vol. 29, no. 8, pp. 607–616, Dec. 2005.

[6] M. Kass and A. Witkin, "Snakes: active contours models," *International Journal of Computer Vision*, vol. 1, no. 4, pp. 321–331, Jan. 1987.

[7] J. Lang, D. K. Pai, and R. J. Woodham, "Robotic acquisition of deformable models," in *Proc. ICRA '02*, vol. 1, 2002, pp. 933 – 938.

[8] V. Caselles, F. Catte, T. Coll, and F. Dibos, "A geometric model for active contours in image processing," *Numerische Mathematik*, vol. 66, no. 1, pp. 1–31, Dec. 1993.

[9] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: a level set approach," *Transactions on Pattern Analysis and Machine Intelligence. IEEE*, vol. 17, no. 2, pp. 158–175, Feb. 1995.

[10] V. Caselles, "Geometric models for active contours," *Image Processing. Proceedings. International Conference on*, vol. 3, pp. 9–12, Oct. 1995.

[11] F. Huang and J. Su, "Face contour detection using geometric active contours," *Proceedings of the 4th World Congress on Intelligent Control and Automation*, June 2002.

[12] C. Harris and M. Stephens, "A combined corner and edge detector," *Proceedings of The Fourth Alvey Vision Conference*, pp. 147–151, 1988.

[13] B. K. Horn, "Closed form solution of absolute orientation using unit quaternions," *Optical Society of America A: Optics, Image Science, and Vision*, vol. 4, no. 4, pp. 629–642, 1987.

[14] A. Gruen and D. Akca, "Least squares 3d surface and curve matching," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 59, no. 3, pp. 151–174, Mar. 2005.

[15] G. Q. Chen, "Robust point feature matching in projective space," *Computer Vision and Pattern Recognition, 2001. CVPR 2001*, vol. 1, pp. 717–722, 2001.

[16] Gruen.A.W, "Adaptive least squares correlation: A powerful image matching technique," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 14, no. 3, pp. 175–187, Mar. 1985.

[17] Z. X. Zhang and J. Q. Zhang, *Digital Photogrammetry*. Wuhan Technique University of Surveying and Mapping, 1997.