Digital Image-Based Elasto-Tomography for Soft Tissue Imaging

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INTRODUCTION

Breast cancer was the leading cause of cancer death among New Zealand women in 1999 [1]. Early detection is of critical importance, as the chances of five-year survival increases to approximately 90% [2]. Mammographic techniques rely variation of tissue density for image contrast, however the contrast between healthy and diseased tissue is relatively low (5% - 10%). The key to elastographic techniques is that they measure the variation in tissue stiffness. For breast tissue this is a high contrast feature with an order of magnitude variation between healthy and cancerous tissue [3].
Emerging techniques in breast cancer screening include mechanical imaging entailing the reconstruction of tissue properties using mechanical sensors on the skin surface [4,5], ultrasound elastography [6], and magnetic resonance (MR) elastography [e.g. 7-15] to obtain 3-D tissue displacement information through out the breast volume. However, MR based elastography has the disadvantage of needing high cost, location specific imaging equipment.

The proposed system uses an actuator to induce sinusoidal motion in the breast tissue at a fixed frequency. The resulting surface motion is quantified using digital imaging sensors, and an elastographic reconstruction of the 3-D breast tissue elastic properties created. An advantage of this digital image based system is that as the fundamental silicon technologies improve in performance, so will the systems capability.

The focus of this paper is on the algorithms for obtaining tissue motion information, however proof of concept simulations are presented for the entire system.

MOTION SENSING

The examination requires the collection of a series of images, wherein motion of objects within the series are analyzed to infer sites where cancer is likely. Digital image based motion sensing for this system requires four major operations.

Filtering and Object Identification

Any image is converted so objects to be identified have significant contrast. The size and shape of an object is determined by the number of coincident object pixels and their organization. Each object is assigned a matrix, referred to as a single object matrix, and a single object matrix from a frame is compared to object matrices from the prior image frame to match the object. Practically, objects could be added to breast tissue by applying a speckle pattern to the breast surface.

Motion Detection

Object motion is determined by comparing the position of an object in a frame with its position in the previous frame using a modified block comparison method. The displacement vector is then determined and the process repeated for every object in the frame, providing a motion vector for several locations from each set of images. This method is reliable and computationally inexpensive compared to other methods such as phase correlation.

Camera Calibration and 3-D Reconstruction

Camera calibration is used to determine the relationship between the fixed global coordinates or object space (**X,Y,Z**) and the local image space (**x,y,z**), whose origin is at the projection centre. A fundamental assumption in the 3D reconstruction process is that a line exists between the projection centre and the object being tracked. Where this line intersects the image plane is called the image point, whose pixel coordinates are (*u,v*). By tracking the motion of this point in two or more images the global motion (*X,Y,Z*) can be reconstructed.

Transforming information from the image coordinate system to the object coordinate system requires more than the rotations and translations known as the extrinsic properties. It also requires the focal length, image plane centre, and the pixel and frame sizes, collectively known as the intrinsic properties. Camera calibration was implemented using basic computer vision functions [16] and a least squares solution.

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \frac{f}{pixel\ \ width} & 0 & u_c & 0 \\ 0 & \frac{f}{pixel\ \ height} & v_c & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad (1)$$

Where f is the focal length of the image, s is a scaling factor, u_c,v_c are the pixel coordinates of the centre of the image plane, r_{ij} are the elements of a (3 x 3) rotation matrix and t_i are the elements of a (3 x 1) translation vector. The camera calibration matrix, $C = [q_{ij}]$, is the product of the two matrices in Equation (1).

Given a set of known calibration points with coordinates in both object and image space, the calibration matrix can be found and it is then possible to find the 3D coordinates of any point in object space.

Sinusoid Fitting

Given a known sinusoidal tissue actuation frequency, the steady state motion is also sinusoidal at the same frequency [9-11]. A singular value decomposition based method can fit the motion data for each measured

location to average out error and obtain a more robust estimate of the motion amplitude and phase. Sampling is done at infrequent intervals that enable the camera to obtain an image and avoid redundant data.

Error Analysis

Error in the 2-D motion tracking process was quantified using a Monte Carlo analysis. Figure 1 shows that error in tracking pixel position does not significantly affect the magnitude of the motion vector obtained.

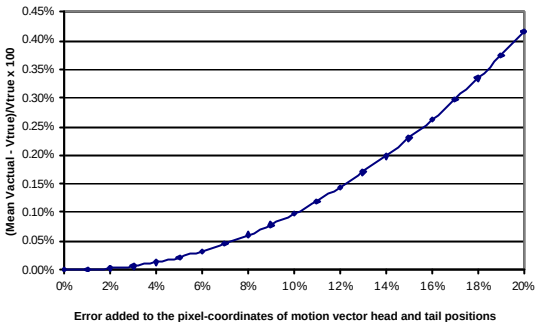

Figure 5: 2-D motion error analysis

PROOF OF CONCEPT SIMULATION

A finite element model of the breast as a hemisphere with a high stiffness centre region creates a simple test case measuring motion at 32 unevenly distributed nodes. The harmonic input is 10mm displacement at 100 Hz and the steady state motion for the measured nodes was put into a CAD program where the motion sensing algorithms developed were used to measure the motion and test the proposed system with a two camera configuration. The average measured motion error is 13.7% primarily due to uncontrolled variation in focal length from the CAD program. The results were put into an elastographic reconstruction routine to identify the 3-D elastic property distribution. The reconstructed properties captured the resulting tissue stiffness values to within 5%, well within the contrast between cancerous and healthy tissue. A second three material problem with a very small region of cancerous tissue was solved with similar results using this method.

CONCLUSIONS

The development of motion sensing algorithms to measure surface tissue motion for a digital image based elasto-tomographic (DIET) soft tissue imaging system are presented and a simple proof of concept simulation performed. This research is part of a larger soft tissue imaging technology.

REFERENCES

[1] Cancer Society of New Zealand, *Causes of Cancer deaths in New Zealand*, 2003.

[2] CC Boring, Squires and Tong, T. "*Cancer Statistics*," CA Cancer J. Clin, 1994;44:7-26.

[3] Australian national breast cancer centre website. www.nbcc.org.au/pages/info/early.htm

[4] T M Krouskup, T Wheeler, F Kallel, B S Garra and T Hall. "*Elastic Modulli of Breast and Prostate Tissues Under Compression*," Ultrasonic Imaging, Vol. 20, pp. 260-274, 1998.

[5] A Sarvazyan, *Mechanical Imaging: a new technology for medical diagnostics*, Int J Med Inf 1998 Apr, 49(2): 195-216

[6] P Chaturvedi, M Insana, T Hall, *Acoustic and Elastic Imaging to Model Disease Induced Changes in Soft Tissue Structure*, Information processing in Medical imaging 15th International conference, IMPI ' 97, Vermont, USA Proceedings.

[7] KM Hitawsky, *Freehand ultrasound elastography of breast lesions: clinical results*, Ultrasound Med Biol 2001 Nov; 27(11): 1461-9

[8] E.E.W. Van Houten, K.D. Paulsen, M.I. Miga, F.E. Kennedy and J.B. Weaver, "*An overlapping subzone technique for MR based elastic property reconstruction*", Magnetic Resonance in Medicine, 1999, 42(4), pp 779-786.

[9] E.E.W. Van Houten, J.B. Weaver, M.I. Miga, F.E. Kennedy and K.D. Paulsen, "*Elasticity reconstruction from experimental MR displacement data: Initial experience with an overlapping subzone finite element inversion process*", Med. Physics, 2000, 27(1), pp 101-107.

[10] E.E.W. Van Houten, M.M. Doyley, F.E. Kennedy, J.B. Weaver and K.D. Paulsen, "*Initial in vivo experience with steady-state subzone-based MR elastography of the human breast*", J of Magnetic Resonance Imaging, 2003, 17(1), pp 72-85.

[11] J.B. Weaver, E.E.W Van Houten, M.I. Miga, F.E. Kennedy and K.D. Paulsen, "*Magnetic resonance elastography using 3D gradient echo measurements of steady-state motion*", Medical Physics, 2001, 28(8), pp 1620-1628.

[12] E.E.W. Van Houten, M.I. Miga, J.B. Weaver, F.E. Kennedy and K.D. Paulsen, *"Three-dimensional subzone-based reconstruction algorithm for MR elastography*", Magnetic Resonance in Medicine, 2001, 45(5), pp 827-837.

[13] E.E.W. Van Houten, K.D. Paulsen, M.M. Doyley, F.E. Kennedy and J.B. Weaver, "*Parameter sensitivity in reconstructive elastic property imaging*", Proceedings of the 1st International Conference on the Ultrasonic Measurement and Imaging of Tissue Elasticity, 2002, 56.

[14] E.E.W. Van Houten, K.D. Paulsen, M.M. Doyely, F.E. Kennedy and J.B. Weaver, "*Confidence interval calculation for nonlinear reconstruction of elastic properties*", Proc 10th Scientific Meeting of the Intl Soc for Magnetic Resonance in Medicine, 2002, 2438.

[15] J Bishop, G Poole, M Leitch, and D B Plewes. "*Magnetic Resonance Imaging of Shear Wave Propagation in Excised Tissue*," Journal of Mag Res Imaging, Vol. 8(6), pp. 1257-1265, 1998.

[16] P Kovesi, *Camera Calibration Stereo and Structural light, Lecture notes and code from website*, School of Computer Science, University of Western Australia.