PRELIMINARY TESTING OF SENSITIVITY TO INPUT DATA QUALITY IN AN ELASTOGRAPHIC RECONSTRUCTION METHOD

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ABSTRACT

An elastographic reconstruction method has been developed to recover the material properties of soft tissue by model-based analysis of image data acquired at different states of mechanical loading. The algorithm utilizes image similarity as part of the cost function for a multi-resolution, non-linear optimization. Previous work with a phantom membrane used for simulated dermoscopic application has prompted this preliminary investigation of the relative effects of additive image noise and boundary condition determination errors on the performance of the method. The results as quantified by elasticity contrast and localization accuracy indicate that the reconstruction process is robust in the presence of realistic levels of image corruption and tolerates the majority of boundary condition mapping errors.

1. INTRODUCTION

The practice of palpating soft tissue structures in the course of the physical exam for assessing tissue health has had a long-standing clinical history of providing correlation between improper stiffness and pathology. The ability to characterize the mechanical properties of tissue is therefore a potential source of information relevant for both diagnosis and prognosis. One way in which this could be achieved in a non-invasive manner is through analysis of tissue deformation with imaging and image processing techniques, which is a central goal of the field of elastography [1].

The conceptual framework for our elastographic reconstruction has been previously described in [2-4]. In brief, images of a tissue of interest are acquired in an initial (source) and then mechanically loaded state (target). The source image is deformed by a prescribed computational model and compared to the target. This is repeated in an iterative process using updates to the elasticity parameters of the model as generated by a multi-resolution, non-linear optimization scheme in order to achieve a suitable match in image similarity. Because the goal of the reconstruction is to determine a spatial mapping of tissue elasticity, this process can also be classified as an inverse problem.

Our observations during the ongoing development and testing of this method have prompted questions concerning the quality of data necessary and sufficient to achieve satisfactory results (i.e. fidelity of the reconstructed elasticity image). The primary inputs to the reconstruction method are the acquired images and the delineated boundary conditions on the region of interest. While it is clearly preferable to have idealized data, in reality, both inputs involve varying levels of manual interaction. As an initial study, we have sought to test the effects of degradation in data quality on the end reconstruction by using additive image noise and randomized boundary condition selection error.

2. METHODS

2.1. Elastographic Reconstruction Framework

There are three major components in the reconstruction framework: a biomechanical model of tissue response to applied deformation, a method of image comparison, and an optimization scheme. For the current version, a continuum-based model of mechanical equilibrium using isotropic Hookean linear elasticity with a plane stress approximation is employed [5]. This allows for a reduction of the general 3D formulation of Cauchy’s Law to the two parameters of Young’s modulus and Poisson’s ratio in 2D. The displacement solution of the finite element representation of the model, solved using the standard Galerkin method of weighted residuals [6], is then applied to the nodes of a simple triangular mesh based on the source image domain in order to perform image deformation. The mesh is partitioned by K-means clustering (MATLAB R14, Mathworks, Nattuck, MA) into N number of regions, each of which describes a distinct set of homogeneous elastic properties for a grouping of adjacent elements. This allows for implementation of the multi-resolution approach by creating a hierarchy of increasingly finer spatial distributions of elasticity parameters, which has been shown to be an improvement upon previous versions using only a
single resolution [2,3]. A second discretization is performed to divide the target image into $M$ number of rectangular zones containing approximately equal numbers of pixels. The deformed source image is compared to the target using an intensity-based image similarity metric (here, the correlation coefficient [7]) in the evaluation of the least squares error objective function

$$\sum_{m=1}^{M} (S_{TRUE} - S_{EST})^2$$

(1)

where $S_{TRUE}$ is an $M \times I$ vector of the (maximum) similarity values achieved when comparing the target image to itself and $S_{EST}$ is the $M \times I$ vector of similarity between the target and model-deformed source image created using current estimates of the elastic modulus distribution. It should be noted that $S_{TRUE}$ has by definition a value of 1 for the correlation coefficient.

The minimization of equation (1) using a Levenberg-Marquardt approach takes the form

$$[J^{T}J + \alpha I] \Delta E = [J^{T}S_{TRUE} - S_{EST}]$$

(2)

where $J$ is the Jacobian matrix of size $M \times N$ estimating $\partial S/\partial E$, $\Delta E$ is the $N \times I$ vectors of updates to the current elasticity values, and $\alpha$ is the scalar regularization term for the Hessian matrix as described in [8].

2.2. Material Preparation and Image Acquisition

For our simulation purposes, a two-material skin phantom had been previously constructed [2] as a thin membrane measuring 15 cm x 15 cm, with a single 5-cm circular stiff inclusion embedded in the center (Figure 1). The phantom was manufactured with Smooth-On™ polyurethanes (Smooth-On, Easton, PA) Evergreen 10 and Evergreen 50. These materials have essentially indistinguishable colors but vary significantly in their elastic modulus values, so the former was used as the bulk material and the latter for the inclusion. Based on material testing, the expected contrast ratio of Young’s modulus values was determined to be approximately 5.7:1. A black permanent marker was used to place a pattern of regularly spaced (~1 cm) grid lines on the membrane. The membrane was clamped along two opposite edges and then stretched in a uniaxial fashion by means of a milling vise. A commercial webcam (Logitech QuickCam Pro 4000) was mounted above the assembly to acquire image pairs of the membrane in pre- and post-stretched states (960 x 1280 pixel resolution, 8-bit grayscale).

2.3. Reconstruction Experiments

Based on prior work, a data set consisting of a particular image pair and associated boundary conditions known to produce a satisfactory reconstruction was designated as the gold standard for the remainder of the experiments (Figure 1). In order to test the effect of increasing amounts of additive noise on the reconstruction algorithm, Gaussian random fields of 1, 5, 10, 15, 20, 25, and 30% noise were applied to the base target image in three separate trials. This presents a challenge that ascertains the ability of the similarity metric and objective function to discern a proper match.

The current method for selecting Dirichlet boundary conditions on the finite element mesh is semi-automated and requires the user to make a final determination on point correspondence. The second experiment was intended to simulate the targeting error of the user (e.g. visual cues and input device control). Each test involved applying randomized vectors of equal magnitude to alter the boundary conditions of the gold standard data set. Errors of 0.1, 0.2, 0.3, 0.5, 0.75, 1.0, 1.5, and 2.0 mesh units (scaled to be equivalent to pixel coordinates) were used in two separate trials for a total of 16 reconstructions. Sub-pixel magnitudes were included after determining that the accuracy of selecting a feature point in the image/mesh was typically less than or equal to 0.5 units for users ranging from moderate to expert skill.

For all reconstructions, resolutions progressing through $N = 16, 36, 64, 144, 256$, and 400 regions and $M = 9$ similarity zones were used; domains were initialized to homogeneous elasticity and Poisson’s ratio held constant at 0.485 to represent nearly incompressible material(s).

2.4. Reconstruction Analysis

The final reconstructed elasticity values were modeled as a mixture of two Gaussian distributions, and a threshold was established to maximize inter-class variation [9] and subsequently classify each region as bulk or stiff material. Because Dirichlet boundary conditions are exclusively used in these reconstructions, the method is only sensitive to relative differences in elasticity. The quantities used in evaluating reconstruction success are the elasticity contrast ratio, localization accuracy of the inclusion, and an overall measure designated the ‘quality of reconstruction score’ (QRS). The elasticity contrast ratio (CR) was calculated...
from the mean values of the two material classes, and the positive predictive value of identifying stiff material within the independently segmented boundary of the inclusion gives a measure of localization accuracy (LA). The quality of reconstruction is simply then the product QRS = CR*LA, which allows the user to consider the other two measures in conjunction.

3. RESULTS

Figures 2 and 3 show examples of reconstructions achieved under various image noise and boundary condition errors, and individual localization errors and contrast ratio values are listed in Table 1. Note that the data for the image noise experiment was averaged from the three trials, and that the data presented for the boundary condition experiment is from one [representative] trial. Figure 4 is a plot of the reconstruction quality decreasing with increasing image noise, and Figure 5 shows the reconstruction quality trend plotted against the change in initial alignment error (detailed in the following section) relative to that of the gold standard.

Table 1. Reconstruction quality under noise conditions

<table>
<thead>
<tr>
<th>% Noise</th>
<th>1</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA</td>
<td>0.92</td>
<td>0.90</td>
<td>0.91</td>
<td>0.70</td>
<td>0.69</td>
<td>0.66</td>
<td>0.56</td>
</tr>
<tr>
<td>CR</td>
<td>3.56</td>
<td>3.45</td>
<td>3.45</td>
<td>3.24</td>
<td>2.88</td>
<td>2.83</td>
<td>2.68</td>
</tr>
</tbody>
</table>

Gold standard: LA = 0.95, CR = 3.60

<table>
<thead>
<tr>
<th>Boundary condition error</th>
<th>AE</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.5</th>
<th>0.75</th>
<th>1.0</th>
<th>1.5</th>
<th>2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA</td>
<td>0.87</td>
<td>0.92</td>
<td>0.88</td>
<td>0.59</td>
<td>0.94</td>
<td>0.86</td>
<td>0.86</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>CR</td>
<td>3.63</td>
<td>3.68</td>
<td>3.44</td>
<td>2.91</td>
<td>3.46</td>
<td>3.71</td>
<td>3.78</td>
<td>3.30</td>
<td></td>
</tr>
</tbody>
</table>

CR = elasticity contrast ratio, LA = localization accuracy
AE = initial alignment error (%), Err = error magnitude.

From visual inspection of Figure 2, it is apparent that the achieved reconstruction becomes more inaccurate with increased image noise. However, the ability to identify and localize the stiff inclusion is not significantly impaired until a noise field of greater than 10% is applied. The threshold was found by determining which level of noise provided the best minimum sum squared error fit of two lines to the distribution of reconstruction quality in Figure 4. This would indicate that the similarity metric and objective function are robust to intensity deviations of about 6 gray levels. While Gaussian noise is one of several possible types and may not always be an ideal model, it is still relevant to acquisition inaccuracy and corruption processes that may be encountered across several medical imaging modalities. The use of an intensity-based similarity metric appears to give the method an advantage in being generally insensitive to reasonably expected amounts of image noise.

4. DISCUSSION

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Figure 3 demonstrates that because of the random nature of the boundary condition errors, the magnitude is itself not an accurate indicator of reconstruction quality. This necessitated the introduction of a more suitable parameter that accounts for the net effect of the altered boundary conditions in order to perform fair evaluations. In essence, randomizing the vectors at every node causes the optimization to use an unpredictable starting pose and increases its chance of converging to an improper minimum. Therefore, the ‘initial alignment error’ (AE) is defined as the relative percent change between the objective function evaluation using the gold standard boundary conditions and those of the test case. An as example, it could be assumed that vectors of magnitude 0.5 would be a much more tolerable error than 2.0, but it is the significantly larger AE...
of the former that actually predicts the poor outcome. However, it should also be noted (results not shown here) that even if the same set of error vectors are scaled over varying magnitudes, there is no clear trend in alignment error or reconstruction quality. This appears to imply that certain boundary nodes, most likely those in the direction of largest strain, have a greater effect on reconstruction and merit particular care in selection. Other factors influencing unfavorable reconstructions are most likely nonlinear effects not predicted by the current model as well as an inherent lack of discrimination by intensity-based similarity metrics in analyzing the regularity of the imposed grid pattern. Nevertheless, for the error magnitudes tested that best approximate realistic inaccuracies (i.e. <0.5 units), the alignment errors were small and quality of the end reconstruction was seen to be quite good. This qualitatively validates the current method of determining point correspondence as a reasonable procedure with an accommodating margin (factor of four) in light of typical user interaction.

5. CONCLUSIONS

In this work, we have presented a method for recovering elasticity parameters from image data of thin membrane structures by maximizing the image similarity between two different states of mechanical loading within the context of an inverse problem. The biomechanical model, multi-resolution optimization, and image acquisition are each modular components of this elastographic reconstruction framework, making it extensible to added sophistication. Tests were conducted to examine the tolerance of the method to degraded or improper inputs. The results indicate that the gold standard data set was mostly optimal for obtaining a successful reconstruction. Widening disparities in either image data or boundary condition selection from that in the gold standard caused observable trends of declining reconstruction quality. Based on these observations, it appears that the method handles most expected variations encountered in image acquisition as well as the majority of typical user inaccuracies. Because there are complicated effects associated with mapping of the Dirichlet boundary conditions in constraining the displacement solution of the model, further study on inter-rater variability in selection as well as comparisons with more automated point correspondence methods is ongoing.

Acknowledgements This work was supported in part by a Whitaker Foundation Young Investigator Continuation Award and the Congressionally Directed Medical Research Program – Breast Cancer Research Program Pre-doctoral Fellowship.

6. REFERENCES