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A novel shape-similarity-based elastography technique for prostate cancer assessment

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Purpose: Association between tissue stiffness alteration and pathology is well known. This has formed the basis for prostate elastography imaging techniques where images of prostate tissue mechanical properties are reconstructed. In this paper, the authors present a novel prostate elastography technique which, unlike other techniques, relies on magnitude image data only.

Methods: This proposed technique works in conjunction with ultrasound or magnetic resonance imaging (MRI) imaging modalities and it requires the prostate’s pre- and postdeformation images as input. It uses a constrained reconstruction method where the elastic moduli of the prostate’s normal and pathological tissues are determined based on an essential subset of the tissue deformation provided by the images data. The elasticity reconstruction technique uses optimization where similarity between calculated and observed shape features of the postcompression prostate image is maximized. The method was validated with an in silico phantom study followed by studies using ultrasound and MR with tissue-mimicking phantoms.

Results: Using the proposed methods, it was observed that the maximum uncertainties of the reconstructed Young’s modulus ratios of tumor to normal tissue were 15.6% and 9.7%, which were obtained from the transrectal ultrasound (TRUS) and MR tissue-mimicking phantom studies, respectively.

Conclusions: This novel prostate elastography technique relies on prostate TRUS or MRI images that can be routinely acquired without additional imaging hardware. The phantom studies provided evidence that the proposed technique has a good potential to reconstruct prostate stiffness maps noninvasively particularly when applied in conjunction with MRI. Further studies are necessary to evaluate the technique’s merits for clinical use.

Key words: prostate cancer, elastography, Young’s modulus, optimization, tissue-mimicking phantom

1. INTRODUCTION

Prostate cancer is the most common cancer in American men after skin cancer and is the second leading cause of cancer death after lung cancer in this group. Prostate cancer is commonly diagnosed and characterized using histopathological analysis of tissue samples acquired using transrectal ultrasound (TRUS) guided needle biopsy. This usually follows detection of a high level of prostate specific antigen in the blood and/or a positive digital rectal examination. The needle guidance relies on B-mode ultrasound, which is not very specific as prostate cancers sometimes appear isoechoic with respect to the surrounding healthy tissue and less than 0.2% of the prostate is typically sampled leading to repeated biopsies. These shortcomings of needle biopsy have motivated many studies aimed at developing methods that can reliably detect prostate cancer. Magnetic resonance imaging (MRI) is the standard of care for detection and assessment of many cancers. Among MRI techniques, T2-weighted MRI has been further explored to identify its potential for prostate cancer diagnosis. Studies have shown that this technique has a sensitivity of 83% and specificity of 62%.

Given the pathological complexities associated with prostate cancer, some research groups took the approach of imaging multiple parameters pertaining to the
prostate tissue with the aim of massing different signatures associated with the disease. This led to the multiparametric MRI imaging techniques which have shown to be promising for improving prostate cancer diagnosis. However, limited availability of multiparametric MRI may limit its routine clinical utility. As a result, researchers have made efforts to develop more clinically viable methods for prostate cancer detection and classification. Among these methods, elastography has attracted significant attention and research efforts.

Alteration of tissue stiffness is associated with pathologies such as prostate and breast cancers. This was demonstrated by stiffness measurement studies of ex vivo prostate tissues conducted by Krouskop et al. and Zhang et al. As such, measurement of the in vivo mechanical properties of prostate inclusions may also be useful for detection and classification of prostate lesions with improved reliability measured by sensitivity and specificity. The general concept in elastography is to induce motion within the tissue by mechanical stimulation while imaging the resulting tissue displacements with modalities such as ultrasound or MRI. Mechanical stimulation can be either quasistatic where the motion is applied in a slow manner (≈1 Hz) or harmonic where a mechanical stimulus applies higher frequency (50–500 Hz) shear and/or compression waves. Some prostate elastography studies that reported the feasibility of this method for prostate cancer diagnosis involved harmonic MR elastography and US elastography. Harmonic elastography techniques require additional devices to generate waves and the constructed shear modulus distribution mainly depends on the waveform and propagation characteristics. Shear wave imaging (SWI) is a more recently developed technique which has shown great promise for imaging tissue elasticity. Clinical studies involving hundreds of prostate cancer patients have demonstrated sensitivity and specificity of 0.90 and 0.88 for SWI (Ref. 38). In the case of quasistatic methods, strain images can be obtained by calculating the spatial derivatives of the tissue displacement. Strain imaging has shown significant promise for prostate cancer detection and diagnosis. The key assumption in strain imaging methods is that tissue stress distribution is uniform. However, the stress distribution is known to be nonuniform, especially in clinical applications. While efficient because of its real-time data acquisition and image visualization, strain imaging is often associated with artifacts resulting from the stress uniformity assumption. Nonetheless, strain values displayed in strain images provide a rough estimate of the tissue elasticity moduli, leading to approximate localization of abnormal tissue regions. These issues led researchers to develop more accurate elastography techniques based on mathematical inversion of measured tissue displacement data. In these techniques, tissue stress distribution is estimated directly or indirectly based on fundamental differential equations governing the tissue mechanics. While some researchers developed methods of direct displacement field inversion for elastic modulus reconstruction, others developed iterative reconstruction algorithms, which involve stress field calculation using finite element methods (FEM). These algorithms require tissue displacement data calculated using acquired ultrasound or MRI raw data. Since the inverse problems involved in the reconstruction are intrinsically ill-posed, the signal-to-noise ratio (SNR) of the displacement data must be sufficiently high to provide reliable results. As an alternative, Miga developed a novel elastography technique, which does not require displacement data for elastic modulus reconstruction. Instead of tissue displacement data, this technique uses two images acquired pre- and postdeformation as input for the elastic modulus image reconstruction. It is noteworthy that the displacement data are somewhat implicit in these two input images. Following this approach, Courtis and Samani proposed an iterative prostate elastography technique, which also uses two pre- and postdeformation prostate images as input for the reconstruction. This technique formulates the elasticity reconstruction problem as an optimization problem with the aim of finding the elastic modulus parameters that lead to maximum similarity between the measured postdeformation image and its corresponding image calculated by deforming the predeformation image using FEM. In the area of intravascular ultrasound, a somewhat similar concept was utilized for atherosclerotic plaque elasticity reconstruction. For this purpose, Baldewsing et al. proposed an optimization algorithm, which varies the shape and stiffness of atherosclerotic plaque components until the computer simulated strain field becomes close to its measured counterpart. Also, Le Floc’h et al. introduced a preconditioning model for determining atherosclerotic plaque morphology, which they used in an optimization framework to reconstruct the plaque’s elasticity. In this paper, we follow a similar approach to introduce a novel elastography method for measurement of Young’s modulus in the prostate. This method requires only pre- and postcompression images of the prostate. Such images can be acquired by TRUS imaging or endorectal T2-weighted MRI. Hence, a conventional US scanner or MRI scanner with endorectal coil is sufficient to develop the proposed elastography system and no additional hardware or software is required for tissue displacement data acquisition. Unlike the technique introduced in Ref. 28, which is based on the overall similarity of two images, this method relies on similarity between the most essential image features including the contours of the prostate capsule and tumors. In other words, this work involves using only a small but essential subset of tissue deformation data in conjunction with image information to determine the elastic modulus of prostate tissue. Unlike conventional techniques that require displacement data acquisition, this method’s novel elastography framework involves processing segmented pre- and postdeformation images of the prostate. This concept leads to an optimization algorithm which determines a set of tissue elastic moduli that maximizes the similarity between segmented prostate capsule and tumor contours in the prostate’s postcompression images and the corresponding contours calculated using FEM. For validation of this method, in silico and tissue-mimicking phantom studies were conducted.

2. METHODS

The proposed technique follows the constrained elastic modulus concept proposed by Samani et al. where
insignificant elastic modulus variability within each tissue type is assumed. In 2D TRUS imaging, the probe pushes against the prostate, leading to tissue deformation. The contours of the undeformed and deformed prostate capsule and tumors represent essential data that characterize the prostate displacement field. These deformed contours depend on the amount and direction of the probe’s loading and elastic moduli of the tissues. Hence, using the undeformed and deformed contours, the tissue elastic properties can be estimated using an optimization algorithm. This algorithm estimates the Young’s modulus distribution and parameters characterizing loading boundary conditions (e.g., TRUS probe displacement) such that the deformed contours calculated using FEM match their observed counterparts. Figure 1 presents a flow chart of the proposed method.

2.A. In silico phantom study

This study includes a computational prostate phantom study where a TRUS imaging procedure was simulated. The study involved four prostate phantom cases with varied tumor locations within the peripheral zone and different values of Young’s modulus for each lesion. A finite element (FE) model of each phantom (including tumor and surrounding tissue) was created including effects of mechanical loading by a TRUS probe using contact problem analysis. The resulting prostate capsule and tumor contours were considered as the observed postcompression contours. Since the proposed method is formulated based on prostate capsule and tumor delineation, image segmentation inaccuracy has a great impact on the reliability of reconstructed tissue stiffness values. While intra- or interexpert variability of prostate capsule segmentation in MR images is not very significant, errors pertaining to MR image limitations in visualizing prostate tumor regions are significant. For example, Anwar et al. reported a median distance of 1.4 mm between prostate tumor contours in MR images and their histopathological findings. Another study involving prostate TRUS imaging showed that significant contouring variability occurs in the anterior region of the prostate capsule. Unfortunately, no data have been reported to quantify the latter errors. To account for these errors with ultrasound images, sets of random noise were added to the reference prostate capsule contours (considering higher errors for the anterior region) and tumor contours, respectively. Each contour of the prostate capsule and tumor was discretized into 120 vertices. Each vertex has a radius relative to the center of its respective prostate capsule or the tumor contour. Gaussian uncertainty with characteristics consistent with those reported in Refs. 31 and 32 was added to these radii. According to Refs. 31 and 32, segmentation uncertainties are higher at the anterior segment of the capsule’s contour compared to its posterior segment. Moreover, segmentation uncertainty of only one segment of the tumor’s contour is significantly higher than that of the rest of the tumor’s contour. Hence, for the prostate capsule, average and standard deviation values of 0.52 and 0.33 mm with a maximum uncertainty of 1.0 mm were added. For the tumor, average and standard deviation values of 1.54 and 0.98 mm with a maximum uncertainty of 3.0 mm were added.

2.B. Tissue-mimicking phantom study

In order to validate the proposed elastography method, two tissue-mimicking phantom studies were conducted. These studies included TRUS and endorectal coil MR imaging of prostate phantoms. The phantoms were constructed using bovine skin gelatin (G9382, Sigma-Aldrich Co. LLC, ON, Canada) and agar (A5306, Sigma-Aldrich Co. LLC, ON, Canada). They consisted of three regions mimicking the prostate capsule, tumor, and surrounding tissue with Young’s modulus values similar to those reported in the literature. Cylindrical samples were also constructed from the gelatin/agar batches used to construct the three tissue-mimicking regions to determine the ground truth Young’s modulus values by independent uniaxial compression tests.

2.B.1. TRUS tissue-mimicking phantom study

Two separate tissue-mimicking phantom studies were conducted to demonstrate the robustness of the proposed technique against image segmentation errors and probe orientation uncertainty, respectively. As shown in Fig. 2, the phantoms used in the studies consist of three regions mimicking the background, prostate capsule, and tumor tissues. To construct each region, gelatin and agar were used with various concentrations to achieve suitable tissue stiffness. Varying amounts of Sigmacel Cellulose (S3504, Sigma-Aldrich

![Fig. 1. Flow chart of the proposed elastography method, which requires the prostate images acquired at two states of pre- and postdeformation as input for elastic modulus reconstruction.](image-url)
Co. LLC, ON, Canada) were added to each phantom part to achieve sufficient image contrast. The concentration of gelatin was 6.0% for all tissues while the concentrations of agar were 1.2%, 2.4% and 3.3–3.6 for the background, prostate capsule, and tumor-tissue-mimicking regions, respectively. Sigmatel concentrations were 1%, 0.8%, and 0.6% for the background, prostate, and tumor tissue-mimicking regions, respectively. Compression of the prostate was applied using displacement of the ultrasound probe as shown in Fig. 2. Pre- and postcompression US images were acquired using an Ultrasonix RP system (Ultrasonix Medical Corporation, Richmond, BC, Canada). A 128-element curvilinear array transrectal ultrasound transducer (BPC8-4/10) was used which spanned the whole prostate. The transmit frequency was 5 MHz and a line density of 128 with an 85% sector width was utilized, permitting 108 lines/frame.

The first phantom study did not involve significant probe orientation variability and care was taken to ensure minimal probe’s pitch angle with the rectum cavity. In the second study, the probe’s pitch angle with the rectum cavity was varied before it was measured. This measurement was carried out using digital images of the phantom being loaded with the probe which was acquired at the instant the postdeformed B-mode image was acquired. The applied angles ranged from −8° to 6° (−8°, −3°, 2°, 4°, and 6°) to include both negative and positive angles. Negative and positive angles correspond to the probe’s handle moving away from and closer to the prostate, respectively.

2.B.2. Endorectal coil MRI tissue-mimicking phantom study

For this study, a phantom similar to the TRUS phantom was constructed (see Fig. 3). Gelatin with a concentration of about 7.5% was used for all tissue-mimicking regions with 1%–3% concentrations of agar to simulate the background, prostate capsule, and tumor regions, respectively. To obtain high quality prostate images, an endorectal MRI coil was placed inside an opening in the phantom, mimicking the rectum. The standard endorectal coil consists of a RF coil for MR reception combined with a flexible rubber balloon, which is inflated after insertion to press the coil against the prostate. Prior to acquisition of the precompression state image, the balloon was inflated with air to the point that very little pressure was applied to the rectal wall. The phantom was imaged in this position and the acquired image was regarded as the precompression image. Postcompression imaging data were acquired after further inflation of the balloon such that the ER coil was pressed against the rectal wall causing significant compression of the prostate capsule. All imaging data were acquired using a GE Healthcare MR750 3.0 T scanner (GE Healthcare, Waukesha, WI) and a 3 T MR-compatible endorectal coil (Medrad, Inc., Indianola, PA). For image acquisition, a $T_2$-weighted fast spin-echo sequence was used with 256x256 mm FOV, 512x512 resolution, 2-mm slice thickness with 2-mm spacing, TR = 15 000 ms, TE = 159 ms, 90° flip angle, echo train length = 20, and NEX = 2.

2.C. Segmentation

As stated earlier, the proposed method follows a constrained elastography approach, which requires knowledge of the geometry of each tissue region. In the tissue-mimicking phantom studies, to account for user variability, prostate capsule and lesions were manually segmented 10 times from the TRUS B-mode or MR imaging data.

2.D. Finite element modeling

After image segmentation, the predeformation image was discretized into a FE mesh before it was analyzed using FEM to obtain its predicted displacement field. The FE mesh of the prostate including the tumors and background tissue was generated using a transfinite interpolation (TFI)-based technique. Different Young’s modulus values were assigned to the three regions mimicking the prostate, the tumor, and...
the background tissue. After FE meshing and setting the boundary conditions and loading, the prostate FE model was analyzed using ABAQUS (Dassault Systèmes Simulia Corp), a FE solver to obtain the postcompression contours of the regions mimicking the prostate capsule and tumors.

### 2.D.1. TRUS finite element modeling

The TRUS probe was inserted into the tissue-mimicking phantom and translated predominantly along the posterior–anterior direction (see Fig. 2) to provide compression of the regions mimicking the prostate, the tumor, and the background tissues. The prostate tissue along with an extended block of background tissue representing background connective tissue was included in the FE model. All points on the block’s edges where the effect of the probe compression becomes insignificant (Saint-Venant’s principle) were assigned fixed boundary conditions. The TRUS probe loading was modeled using a contact model between the probe’s rigid body and the prostate block where the contact was between the probe’s surface and rectal wall. Prescribed displacement boundary conditions consistent with the probe’s motion were used. The displacement magnitude and direction were considered unknown and had to be determined through the optimization algorithm used for elasticity reconstruction.

### 2.D.2. Endorectal MRI finite element modeling

Mechanical stress was applied to the phantom’s rectal wall by means of the coil’s balloon inflation. Since the amount of the applied pressure is unknown in the experimental setup (and for in vivo imaging for that matter), prescribed radial displacements’ boundary conditions were used to model the corresponding loading. These radial displacements were determined by extending radial lines from the centroid of the rectum’s opening on the MR images to cross the segmented contours in the pre- and postdeformation images. The radial distance between the two contours at each nodal (crossing) point was used as the prescribed displacement vector at that point. Again, the prostate capsule along with a block of background tissue was incorporated such that all points on the background block’s edges were assumed to be fixed.

### 2.E. Young’s modulus reconstruction

By obtaining the postcompression prostate capsule and tumor contours using FEM, Young’s moduli of the prostate and tumor can be found by optimization using the following cost function:

\[
\text{Cost Function} = ||\Gamma_{\text{FEM,}p} - \Gamma_{\text{true,}p}|| + ||\Gamma_{\text{FEM,}t} - \Gamma_{\text{true,}t}||, \quad (1)
\]

where \(\Gamma_{\text{FEM,}p}\) and \(\Gamma_{\text{FEM,}t}\) represent the FEM-generated postcompression prostate capsule and tumor contours and \(\Gamma_{\text{true,}p}\), and \(\Gamma_{\text{true,}t}\) represent their ground truth counterpart contours obtained from the postcompression B-mode image of the prostate. The absolute values \(||.||\) indicate a Euclidian norm. It should be noted that \(\Gamma_{\text{FEM,}p}\) and \(\Gamma_{\text{FEM,}t}\) are functions of \(E_t, E_p, \) and \(E_b\) which are the Young’s moduli of the tumor, prostate, and background tissues, respectively. They are also functions of the loading. As stated earlier, the TRUS probe’s loading was modeled using contact modeling with the probe’s mechanical loading as a prescribed displacement boundary condition with unknown magnitude \((dl)\) and angle \((\theta)\) in the plane of compression. It is noteworthy that minimizing the cost function yields the relative Young’s modulus values of \(E_t/E_p\).

Obtaining the absolute Young’s modulus values requires force data, which could be acquired using force sensors in the experimental setup. The constructed Young’s modulus ratios are still expected to provide valuable diagnostic information. The relative Young’s modulus value, \(E_t/E_p\), can be obtained using the following equation:

\[
\frac{E_t}{E_p} = \frac{\text{argmin}_{E_t,E_p,E_b,dl,\theta} \left[ ||\Gamma_{\text{FEM,}p} - \Gamma_{\text{true,}p}|| + ||\Gamma_{\text{FEM,}t} - \Gamma_{\text{true,}t}|| \right] }{||\Gamma_{\text{FEM,}t} - \Gamma_{\text{true,}t}||}. \quad (2)
\]

This is an optimization problem, which can be solved using optimization algorithms such as Nelder–Mead’s simplex algorithm. Accordingly, the step-by-step reconstruction algorithm can be summarized as follows after constructing the FE model of the prostate and tumor using the TFI technique:

1. Initialize values for \(E_t, E_p, E_b, dl,\) and \(\theta\).
2. Pass the FE model with the current estimates of \(E_t, E_p, E_b, dl,\) and \(\theta\) to the FEM solver (e.g., ABAQUS) to obtain deformed contours of the prostate and tumor.
3. Calculate the cost function using Eq. (1).
4. If the cost function does not satisfy the conditions of the Nelder-Mead’s simplex optimization method, update \(E_t, E_p, E_b, dl,\) and \(\theta\) and return to step 3.
5. If convergence is achieved, stop.

### 3. RESULTS

As mentioned in Sec. 2, the proposed technique was first validated using an in silico phantom study followed by tissue-mimicking phantom studies. Results of these studies are reported in Secs. 3.A–3.C.

Table 1. Reconstruction results of the in silico phantoms assuming no segmentation errors.

<table>
<thead>
<tr>
<th>Case</th>
<th>(E_t/E_p)</th>
<th>(dl) (mm)</th>
<th>(\theta) (rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.75</td>
<td>2.90</td>
<td>-0.08</td>
</tr>
<tr>
<td>2</td>
<td>2.75 (0%)</td>
<td>2.90 (0%)</td>
<td>-0.08</td>
</tr>
<tr>
<td>3</td>
<td>2.77</td>
<td>2.70</td>
<td>-0.07</td>
</tr>
<tr>
<td>4</td>
<td>2.72</td>
<td>3.40</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>2.72 (0%)</td>
<td>3.40 (0%)</td>
<td>-0.02</td>
</tr>
<tr>
<td>5</td>
<td>2.64</td>
<td>3.00</td>
<td>+0.05</td>
</tr>
<tr>
<td>6</td>
<td>2.64 (0%)</td>
<td>3.00 (0%)</td>
<td>+0.05 (0%)</td>
</tr>
</tbody>
</table>

Medical Physics, Vol. 42, No. 9, September 2015
3.A. In silico phantom study

The reconstruction algorithm, with ABAQUS as the FEM solver, was run for each in silico phantom to obtain the Young’s modulus ratio of tumor to prostate tissue. Results obtained for the four phantom cases where segmentation errors were not considered are summarized in Table I. This table provides reconstructed relative Young’s modulus values for $E_t/E_p$. Based on these results, there are no uncertainties for calculated $E_t/E_p$, $dl$, and $\theta$ values. Results corresponding to the same phantoms with the simulated segmentation errors are summarized in Table II. These results indicate that the average errors for $E_t/E_p$, $dl$, and $\theta$ are 21.2%, 15.3%, and 11.7%, respectively. This confirms the importance of image segmentation accuracy in the proposed reconstruction algorithm.

3.A.1. Weight factor effect

The reconstructed $E_t/E_p$ values indicate that significant amount of accuracy was lost by reconstructing the values considering segmentation uncertainties. In order to improve the accuracy of the results, we examined the following weighted cost function for the optimization:

$$
\left( \frac{E_t}{E_p} \right) = \arg\min_{E_t, E_p, dl, \theta} \left[ \omega \| \Gamma_{FEM,t} - \Gamma_{true,t} \| + (1 - \omega) \| \Gamma_{FEM,p} - \Gamma_{true,p} \| \right],
$$

where $\omega$ is a weighting factor used to adjust the capsule’s contour importance with respect to that of the tumor. In order to find the optimal $\omega$, it was incrementally varied from 0.1 to 0.9 with increments of 0.05. The value corresponding to the minimum Young’s modulus reconstruction error was considered to be optimal. The results obtained for the four phantom cases where segmentation errors were considered are summarized in Table III. For each $\omega$, the average uncertainties were calculated based on the difference between the ground truth values and the corresponding reconstructed values for the four cases. This analysis indicated that there was a good compromise between the Young’s modulus reconstruction uncertainties of tissues mimicking the tumor and prostate capsule for $\omega = 0.75$ where the average uncertainties for $E_t/E_p$ were minimum at 14.5%.

3.B. TRUS tissue-mimicking phantom study

Each of the phantom’s pre- and postcompression 2D TRUS B-mode images shown in Fig. 4 was manually segmented 10 times to determine their contours. A FE model was then generated from the precompression image contours. The elasticity reconstruction technique was then employed to reconstruct ratios of the elasticity moduli. For the first

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**Table II.** Reconstruction results of the in silico phantoms including segmentation errors.

<table>
<thead>
<tr>
<th>Case</th>
<th>$E_t/E_p$</th>
<th>$dl$ (mm)</th>
<th>$\theta$ (rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Nominal value</td>
<td>2.75</td>
<td>2.90</td>
<td>-0.08</td>
</tr>
<tr>
<td>Reconstructed value (% error)</td>
<td>2.09 (24.0%)</td>
<td>3.21 (10.7%)</td>
<td>-0.07</td>
</tr>
<tr>
<td>2 Nominal value</td>
<td>2.77</td>
<td>2.70</td>
<td>-0.07</td>
</tr>
<tr>
<td>Reconstructed value (% error)</td>
<td>2.27 (18.0%)</td>
<td>3.35 (24.0%)</td>
<td>-0.08</td>
</tr>
<tr>
<td>3 Nominal value</td>
<td>2.72</td>
<td>3.40</td>
<td>-0.02</td>
</tr>
<tr>
<td>Reconstructed value (% error)</td>
<td>2.19 (19.5%)</td>
<td>3.83 (12.6%)</td>
<td>-0.02</td>
</tr>
<tr>
<td>4 Nominal value</td>
<td>2.64</td>
<td>3.00</td>
<td>+0.05</td>
</tr>
<tr>
<td>Reconstructed value (% error)</td>
<td>2.03 (23.1%)</td>
<td>3.42 (14.0%)</td>
<td>+0.04 (20.0%)</td>
</tr>
</tbody>
</table>

**Table III.** Reconstruction results of the proposed phantom study for different weighting factors where segmentation errors are considered.

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>Average $E_t/E_p$ uncertainty (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>38.1</td>
</tr>
<tr>
<td>0.15</td>
<td>32.9</td>
</tr>
<tr>
<td>0.20</td>
<td>30.8</td>
</tr>
<tr>
<td>0.25</td>
<td>28.6</td>
</tr>
<tr>
<td>0.30</td>
<td>27.7</td>
</tr>
<tr>
<td>0.35</td>
<td>23.2</td>
</tr>
<tr>
<td>0.40</td>
<td>22.1</td>
</tr>
<tr>
<td>0.45</td>
<td>21.2</td>
</tr>
<tr>
<td>0.50</td>
<td>17.6</td>
</tr>
<tr>
<td>0.55</td>
<td>18.8</td>
</tr>
<tr>
<td>0.60</td>
<td>21.2</td>
</tr>
<tr>
<td>0.65</td>
<td>17.6</td>
</tr>
<tr>
<td>0.70</td>
<td>14.5</td>
</tr>
<tr>
<td>0.75</td>
<td>14.2</td>
</tr>
<tr>
<td>0.80</td>
<td>15.2</td>
</tr>
<tr>
<td>0.85</td>
<td>14.8</td>
</tr>
<tr>
<td>0.90</td>
<td>16.1</td>
</tr>
</tbody>
</table>

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Fig. 4. B-mode US images of a prostate phantom with 7-cm fan depth at predeformation (left) and postdeformation (middle) states, and corresponding FE model (right) including the FE mesh and contacting probe. Contours obtained by segmenting regions mimicking the prostate capsule and tumor are also shown.
tissue-mimicking phantom study, the uniaxial compression test performed on the cylindrical samples produced Young’s modulus values of 25, 43, and 110 kPa for the background, the prostate capsule, and the tumor tissue-mimicking samples, leading to \( E_t/E_p \) ratio of 2.56. Due to technical limitation, the stiffness of the surrounding tissue in this experiment is larger than the surrounding tissue in human anatomy.

In order to investigate the sensitivity of the reconstruction technique with respect to small manual segmentation errors, contours of the regions mimicking the prostate capsule and tumor tissues corresponding to the two pre- and postdeformation states were delineated ten times by segmenting their 2D B-mode images manually. The shape similarity-based reconstruction method was then applied using the optimal \( \omega \) value of 0.75 with each of these input contours. Average uncertainty for \( E_t/E_p \) was determined at 11.5\% ± 1.7\%. These uncertainties were obtained using the ground truth modulus values obtained from the uniaxial tests. Next, the more realistic segmentation errors described earlier were included. Here, errors with maximum amplitudes of 1.0 mm were introduced to the reference prostate capsule while errors with maximum amplitudes of 3.0 mm were added to the tumor contours. The reconstruction uncertainties in this case were calculated at 15.6\% for \( E_t/E_p \).

For the second set of tissue-mimicking phantom experiments, which were performed to assess the impact of probe loading orientation uncertainty, Young’s modulus ratio reconstruction was also carried out and results compared to corresponding experimental values. Uniaxial tests lead to Young’s modulus values of 25, 41, and 85 kPa, for the background, the prostate capsule, and the tumor tissue-mimicking regions, respectively, yielding \( E_t/E_p \) ratio of 2.1. Young’s modulus ratio reconstruction was carried out using data corresponding to the induced pitch angles ranging from \(-8^\circ\) to \(6^\circ\). With including realistic segmentation errors, this reconstruction led to \( E_t/E_p \) ratio of 1.8 ± 0.1 which indicates uncertainty of 16.7\% ± 3.4\%.

### 3.C. Endorectal MRI tissue-mimicking phantom study

Figure 5 shows contours of regions mimicking the prostate capsule and tumor tissues, which are obtained by segmenting the phantom’s pre- and postdeformation \( T_2 \)-weighted MR images. The uniaxial compression test performed on the cylindrical samples described in Sec. 2 produced Young’s modulus values of 26, 39, and 76 kPa for the tissues mimicking the background, prostate capsule, and tumor, yielding \( E_t/E_p \) values of 1.95.

A FE model was generated using the contours of regions mimicking the prostate capsule and tumor from the pre-compression image. Next, the proposed method was applied to reconstruct the relative elasticity moduli. Similar to the US phantom study, in order to investigate the sensitivity of the reconstruction technique with respect to small manual segmentation errors, contours of regions mimicking the prostate capsule and tumor tissues corresponding to the two pre- and postcompression states were delineated ten times by manually segmenting their MR images. It is noteworthy to point out that due to the higher inherent contrast of the MRI image, there is little uncertainty about the capsule’s contour. Next, the shape similarity-based reconstruction method was applied with each of these input contours. The average uncertainty of the reconstructed \( E_t/E_p \) was calculated at 5.4\% ± 2.1\%. To assess the reconstruction uncertainties in more realistic scenarios, as discussed earlier, segmentation errors with maximum amplitudes of 1.0 mm were introduced to the reference prostate capsule. Segmentation errors with maximum amplitudes of 3.0 mm were also introduced to the tumor contours. The latter exceeds the 1.4-mm median value reported in the literature significantly. These errors led to reconstruction uncertainties of 9.7\% for \( E_t/E_p \) corresponding to the weighting factor 0.75.

### 4. DISCUSSION AND CONCLUSIONS

In this paper, a novel prostate elastography technique was proposed. The advantage of this technique lies in its modest requirements, as it requires comparison of two prostate images, pre- and postdeformation. This means that a conventional US or MR scanner can be used to acquire image data for the proposed elastography system without additional hardware or software for tissue displacement data acquisition. An important feature of this technique is that it does not require
information of prostate loading. For example, when applied in conjunction with TRUS imaging, the magnitude and direction of the probe displacement with respect to the prostate are unknown parameters, which are obtained through optimization. When applied with endorectal MRI, the loading is included as a prescribed boundary condition, which is calculated from the pre- and postdeformed prostate images. The proposed method is a constrained method where the underlying assumption is that the Young’s modulus of each tissue is uniform within its volume. The reconstruction algorithm was formulated based on an inverse problem approach, which led to an optimization framework. The essence of this algorithm is to find the Young’s modulus values for prostate and tumor tissues such that the similarity between the calculated and observed prostate capsule and tumor contours is maximized. To obtain these contours, image segmentation is required. This implies that compared to traditional elastography, this technique substitutes image segmentation with the RF data processing in US imaging or phase imaging in MRI required for displacement data acquisition. It is noteworthy that the segmented contours of the prostate capsule and tumors under the two states of pre- and postdeformation contain essential tissue displacement information. The proposed optimization algorithm involves FEM analysis in each iteration to obtain tissue deformation corresponding to the current parameters estimate. While the proposed method is conceptually similar to the mutual information based elastography technique introduced by Miga, it differs in the fact that it focuses only on a portion of the image information and, therefore, it is presumably a faster and less demanding method. This may be advantageous for two reasons: (1) it is computationally less intensive and (2) it is less prone to convergence to local minima. An in silico phantom study and two tissue-mimicking phantom studies were conducted to assess the proposed method. To assess the impact of prostate capsule and tumor contour errors introduced by TRUS image segmentation, random errors were added to the known contour vertices for the in silico phantoms. Another numerical experiment was conducted where the weight of the two terms in the cost function, which represent the similarity between the contour pairs of regions mimicking the prostate capsule and tumor, was varied to determine the optimal weighting factors. It was concluded that weighting factors of 0.75 were optimal. As shown in Table III, \( \omega = 0.9 \) led to a reconstruction error of 16.1%. Such weight factor implies a small weight of only 0.1 for the tumor segmentation term in the cost function of Eq. (3) which is suitable for cases with high uncertainty in tumor segmentation. The table shows that in such cases, acceptable error in the reconstructed \( E_t / E_p \) value is still anticipated. This was later confirmed using the tissue-mimicking phantom study where realistic segmentation errors were introduced. In the TRUS tissue-mimicking prostate phantom study, pre- and postdeformation TRUS images were obtained and used as input with the proposed method. In the endorectal MRI tissue-mimicking phantom study, high quality pre- and postdeformation MR images were obtained utilizing an endorectal coil. Compared to results obtained from the TRUS, tissue-mimicking prostate phantom study results obtained from the MRI tissue-mimicking phantom study were more accurate. This can be attributed to the fact that with the MRI phantom study, there is less uncertainty with determination of feature contours and loading information compared to the TRUS phantom study. Results suggest that the proposed method can reconstruct \( E_t / E_p \) values with uncertainties of 15.6% and 9.7% with TRUS and MRI imaging, respectively. These uncertainties, which were obtained with realistic segmentation uncertainties for the TRUS and MRI modalities, are well within the range of reported reconstruction error values. For example, Chopra et al. validated their prostate harmonic MR elastography method with a tissue-mimicking phantom study using dynamic mechanical analysis test, and they reported reconstruction error of \( \sim 20\% \). Parker et al. validated their prostate harmonic US elastography method with ex vivo prostate tissue samples using stress relaxation tests where they reported elasticity reconstruction error of \( \sim 10\% \). Also, Samani et al. validated their breast quasistatic MR elastography method with a tissue-mimicking phantom study where they reported reconstruction error of \( \sim 12\% \). Based on Krouskop et al. measurements, there is a contrast of 3.4 between normal prostate tissue elasticity and cancerous tissue elasticity. If the Young’s modulus ratio reconstruction uncertainties obtained in the phantom study are considered, the contrast would decrease to 2.9 and 3.1 for TRUS and MR imaging, respectively. These values are still sufficient for discriminating cancerous tumors from normal prostate tissue, especially considering that the purpose of the proposed technique is minimizing unnecessary needle biopsies and not as a substitute for needle biopsy. It is noteworthy that the major objective of this study is to provide a proof-of-concept for the proposed elastography method and to assess its relative effectiveness for US and MR imaging modalities. While the small sample size used in this study is sufficient for this purpose, further studies are required to assess the method’s accuracy and sensitivity to various imaging parameters with a higher degree of certainty. The proposed technique requires sufficient image quality to perform segmentation, especially to delineate the tumor boundary. Such quality may not be always available with prostate TRUS images. However, this study indicated the accuracy of the reconstruction technique is greater when used in conjunction with high quality imaging modalities (e.g., MRI). In addition to segmentation errors, the proposed technique involves assumptions and simplifications that may impact its expected accuracy. Specifically, the technique assumes a 2D plane strain problem, which ignores out-of-plane strains. It also considers radial and in-plane displacement boundary conditions with the endorectal MR elastography case. Moreover, it assumes insignificant elastic modulus variation within the volume of each tissue type (tumor, prostate capsule, and surrounding tissue). Finally, minor anatomical structures such as the urethra within the prostate were ignored in the idealized prostate model.

Another potential application of the proposed technique is biomechanical simulation of the prostate, which requires having accurate elastic moduli of tissues to achieve reliable results. As the proposed method is capable of obtaining these moduli in vivo, it can be used in applications that involve
biomechanical simulation of the prostate. Examples of such applications include virtual reality (VR) systems of prostate surgery and computer-aided prostate intervention. Unifocal prostate cases were studied in this work. As the concept is not limited to the number of inclusions, the technique can be extended to reconstruct elasticity modulus of multifocal tumor cases by adding more similarity terms in the objective function. It is also noteworthy that the concept can be also extended to other types of cancer such as breast cancer where US or MRI images of the breast under two states of pre- and postdeformation are available.

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