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Synthetic Elastography from B-Mode ultrasound through Deep Learning

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***Abstract*—Tissue elasticity can be locally estimated using shear-wave elastography (SWE), an advanced technique that measures the speed of laterally-traveling shear waves induced by a sequence of acoustic radiation force "push" pulses. However, SWE is not available on all ultrasound machines due to e.g. power, equipment, and procedural requirements; in particular, wireless devices would face challenges delivering the required power. Here, we propose a fully-convolutional deep neural network for the synthesis of an SWE image given the corresponding B-mode (side-by-side-view) image.Fifty patients diagnosed with prostate cancer underwent a transrectal SWE examination with SWE imaging regions chosen such that they covered the entire or parts of the prostate. The network was trained with the images of 40 patients and subsequently tested using 30 image planes from the remaining 10 patients. The neural network was able to accurately map the B-mode images to sSWE images with a pixel-wise mean absolute error of 4.8 kPa in terms of Young's modulus. Qualitatively, tumour sites characterized by high stiffness were mostly preserved (as validated by histopathology). Despite the need for further validation, our results already suggest that deep learning is a viable way to retrieve elasticity values from conventional B-mode images and can potentially provide valuable information for cancer diagnosis using devices on which no SWE imaging is available.**

***Index Terms*—Deep Learning, B-mode Ultrasound, Shear-Wave Elastography, Convolutional Neural Networks**

I. Introduction

Imaging of tissue elasticity plays a significant role in several applications such as the characterization of prostate cancer [1], liver lesions [2], thyroid nodules [3], breast lesions [4], and the investigation of musculoskeletal abnormalities [5]. In recent years, a number of ultrasound-based technique have been developed to assess tissue elasticity, ranging from quasi-static ultrasound strain imaging using the probe as manual pressure source to more advanced dynamic elastography in which "push" pulses are used to apply stress [6]. Shear-wave elastography (SWE) [7] and acoustic radiation force imaging (ARFI) [8] are examples of the latter category of elastography techniques. By assessing the tissue displacement in response to the "push" pulse, these methods can map the local Young's modulus of tissue operator-independently.

SWE has shown promising results in numerous biomedical fields, but it remains dependent on ultrafast imaging schemes (i.e. frame rates $>$1000 Hz), requires well-equipped transducers, and operators have to be aware of the settling times needed for the generation of reliable elastograms [9], [10]. Therefore, we propose the use of deep learning [11] to infer the elastograms from standard B-mode ultrasound images. The resulting synthetic SWE (sSWE) images can possibly be used for elasticity-like tissue typing.

II. Materials and Methods

A. Regression network architecture

A convolutional neural network was designed and trained to generate sSWE images using B-mode images as input. For this, an encoding architecture has been adopted comprising 3×3-convolutional layers interspersed with 3 max-pooling operations, followed by an inverse decoding architecture. Skip connections were constructed to avoid loss of resolution and vanishing gradients [12], and leaky rectified linear units were implemented to also mitigate the problem of vanishing gradients, and to prevent nodes from settling with zero weight [13]. The final output layer consisted of a sigmoid function that mapped the network output to normalized Young's moduli, as it is most sensitive around 0.5 and thus to the SWE values in the clinically-relevant range for our application [14].

The weights in network were trained in mini-batches using the Adam stochastic optimization method [15], employing the root-mean-square error as the loss function being minimized. The training phase was optimized by choosing a relatively small mini-batch of 64 size and the application of a adaptive learning rate reduction strategy based on the loss reaching a plateau. Data augmentation [16] and drop-out layers [17] were implemented to aid the training generalizability.

B. Data acquisition

For this study, we collected the SWE images of 50 prostate-cancer patients at the Martini Clinic in Hamburg, Germany. Using an Aixplorer$^{\text{TM}}$ (SuperSonic Imagine, Aix-en-Provence, France) equipped with an SE12-3 probe, at least 3 full-prostate images per patient were obtained, in the base, mid, and apex sections of the prostate. The Young's modulus and corresponding confidence maps were extracted from the imaging, along with the side-by-side-view B-mode images of the same region. These images were subsequently normalized for the analysis. Imaging of the first 40 patients was used to train the network, whereas the images of the 10 remaining patients served as

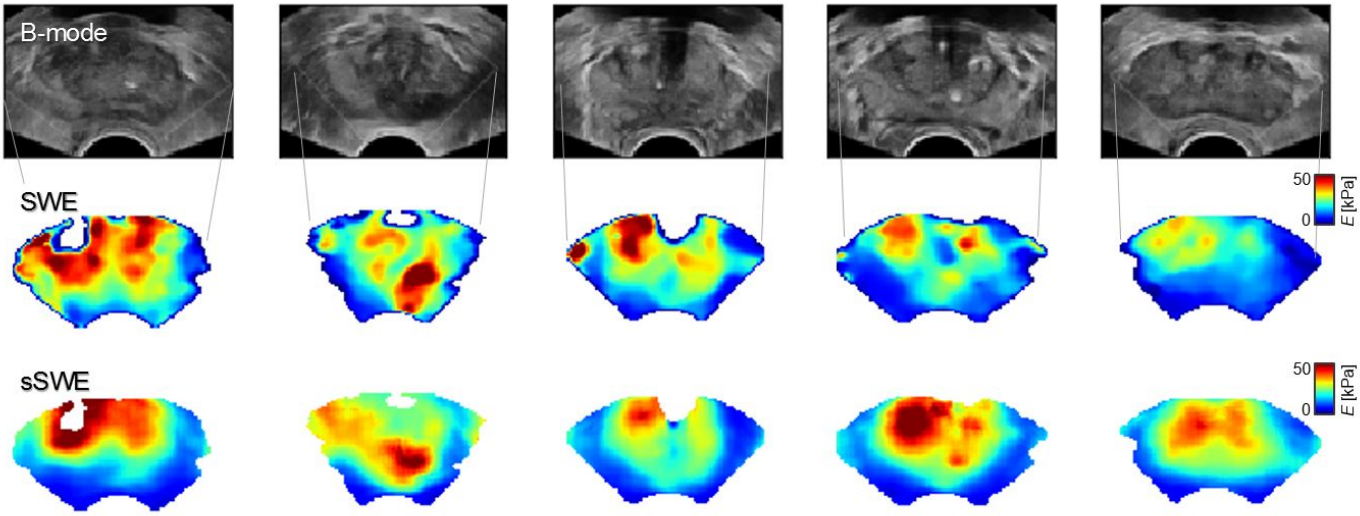

Fig. 1: Examples from five test patients, with (above) the B-mode ultrasound image, (middle) the shear-wave elastographic acquisition, and (below) the corresponding synthetic SWE image by deep learning.

the test set. The mean absolute error over all pixels with an SWE estimate of sufficient quality (i.e., confidence: >75%) was used as the primary performance measure.

III. Results

Obtaining a mean absolute error of 4.8 kPa in Young's modulus, the sSWE procedure was shown able to replicate SWE elastograms with an error below 10% of the elasticity values normally found in the prostate [14]. In Fig. 1, SWE and sSWE imaging of 5 test-set patients are shown.

IV. Discussion and Conclusion

In this work, a deep-learning network is proposed that is able to perform elasticity-like characterization based on conventional B-mode acquisitions. Trained and tested with imaging of the prostate, sSWE was shown to replicate SWE elastograms with good agreement. These results are an indication that there might be a link between the echogenic patterns as encountered in B-mode imaging and the elasticity as assessed during SWE.

The major benefit of sSWE is in that it alleviates the need for high-end ultrasound equipment and can be used in devices that do not meet standard SWE requirements. Moreover, sSWE can be performed retrospectively, reducing procedure times. In the future, sSWE could for example serve as a quick way to add clinically-valuable information on prostate tissue to a multiparametric ultrasound imaging approach of e.g. prostate cancer [18]. Moreover, elasticity-related properties such as viscoelasticity [19], [20] could be considered as a potential secondary output of an sSWE network.

The current study is limited by the relatively small dataset. Therefore, it remains to be investigated how generalizable these results are with looser standardization of imaging, when employed in other organs, or performed using other ultrasound scanners. Although we strive to validate our algorithm in a larger, preferably multicentre dataset to ensure generalizability, our results demonstrate the technical feasibility and promise of SWE elastogram synthesis based on regular B-mode ultrasound.

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