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# DEEP LEARNING ENABLES ACCURATE ESTIMATION OF TISSUE DEFORMATION *IN VIVO*

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## INTRODUCTION

Measuring tissue deformations using medical images allows researchers to noninvasively track tissue mechanics with degeneration or rehabilitation. Researchers have used *image texture correlation* algorithms to compare pixel intensities between successive images and calculate the displacement field between pixels, which is then numerically differentiated to obtain a strain field. These techniques have been applied in various contexts, including quantifying forces in myocardial cells,[1] detecting breast cancer,[2] and studying impact of disease on tissue mechanics *in vitro*.[3] However, these algorithms often struggle with *in vivo* images, partly due to low signal-to-noise ratio and out-of-plane motion.[4] Therefore, the objective of this study was to develop a new technique using deep learning (called `StrainNet`) to accurately predict tissue deformation and ignore image artifacts (*e.g.*, noise). We hypothesized that `StrainNet` would outperform traditional image texture correlation algorithms on synthetic images with known deformations and a real dataset of a wrist flexor tendon undergoing contraction *in vivo*. Our results showed that `StrainNet` reduced error by up to 84% when compared to traditional image texture correlation algorithms in the synthetic datasets. Moreover, the measurements made by `StrainNet` in the *in vivo* experiments were strongly correlated with the measured grip force distributed to the wrist flexor tendons.

## METHODS

**Experimental Procedure.** To investigate *in vivo* tendon mechanics, a participant was asked to perform maximum voluntary contraction (MVC) of their forearm using an IRB-approved protocol (IRB-2020-497). A dynamometer was used to track and measure applied forces during contraction, and the MVC was calculated as the average of three trials. Next, the participant was instructed to contract their forearm to 10%, 30%, or 50% of their MVC in three seconds, hold the contraction for five seconds, and relax their forearm in three seconds. High-frequency ultrasound images (Vevo3100, FUJIFILM VisualSonics Inc., Toronto, Ontario, Canada) of the participant's *flexor digitorum superficialis* tendon were collected throughout the contraction and release. This protocol was repeated five times for each effort level, resulting in a total of 15 trials.

**Synthetic Test Cases.** To test the accuracy of our strain analysis method on a dataset with known deformations, five synthetic test cases were created by artificially imposing a non-linear strain field onto collected ultrasound images. These test cases simulated the process of contraction and relaxation in our experimental procedure described above. Additionally, the prescribed non-linear strain field was designed to reflect reported observations for *in vivo* tendon mechanics. Specifically, the strain in the superficial layer was set to 75% of the deep layer,[5] and the tendon was modeled as an incompressible material.[6,7] The five test cases differed in their maximum longitudinal strain, $\epsilon_{long}^{max}$, which was set to 4%, 7%, 10%, 13%, and 16% to cover the range of strains observed *in vivo*.[5,7–9] Noise was added to all synthetic test cases to simulate the level of noise present in the experimental dataset. By using synthetic test cases with known deformations, we were able to compare the performance and accuracy of our deep learning based approach with existing texture correlation algorithms.

**StrainNet**. `StrainNet` is a deep learning model designed to predict 2D Lagrangian strain from a sequence of ultrasound images of the wrist flexor tendon. It consists of a two-stage architecture, with the first stage classifying the type of bulk deformation present in the image pair (tensile, compressive, or rigid-body) and the second stage predicting the strains throughout the image. To train the model, a set of synthetic images with random deformations was utilized. The deformations in these images were generated using a generalized mathematical model of tendon mechanics,

with the governing parameters being randomly varied to produce a diverse range of strain distributions (*e.g.*, 2% - 20% bulk strain in the longitudinal direction). The training set included 1,000 images in tension, 1,000 images in compression, and 1,000 images undergoing rigid deformation. The model was trained using the Adam optimizer for 100 epochs, allowing it to learn the patterns and features associated with different types of deformation and accurately predict strain in unseen images.

**Data Analysis and Statistics.** `StrainNet`, digital image correlation (DIC),[10] and direct deformation estimation (DDE)[11] were applied to synthetic test cases and experimental images. For the synthetic test cases, the strain error was calculated as the $\ell_2$-norm between the ground truth strain tensor and the algorithm-predicted strain tensor. A pairwise permutation test was conducted on the median strain error for each of the five test cases, with significance set at $p \leq 0.05$. For experimental images, the true strain was unknown, so the analysis was limited to a qualitative assessment. However, linear regression was conducted between the maximum longitudinal strain predicted by the three algorithms during contraction and the percentage of MVC. A strong correlation was defined as an $|r| > 0.7$.

## RESULTS

Of the 15 trials conducted, two trials were discarded due to corruption of data file containing the forces measured by the dynamometer.

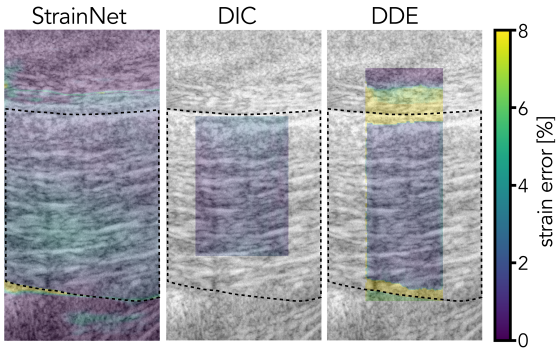


**Figure 1: Spatial distribution of errors incurred by `StrainNet`, DIC, and DDE during maximum contraction in the synthetic test case with maximum longitudinal strain of 10%. Black dashed line represents the boundary between the flexor tendon and the surrounding soft tissue.**

In the synthetic test cases, errors were largest at the boundary between the tendon and surrounding tissue. `StrainNet` achieved pixel-wise strain estimation while DIC and DDE were limited to the central area of interest (**Fig. 1**). The median strain error from `StrainNet` was 48-84% lower than the strain error from both DIC and DDE (**Fig. 2**; $p$<0.001 in all strain cases).

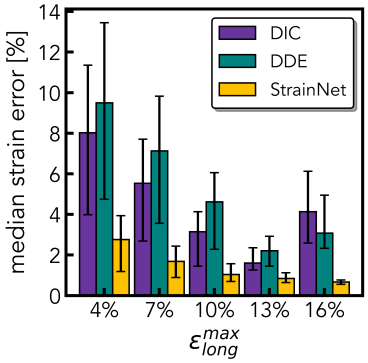


**Figure 2: Median strain error across all five synthetic test cases. Median strain error was statistically significantly lower than DIC and DDE across all test cases ($p < 0.001$).**

For the real experimental images, both DIC and DDE underperformed and many pixels were lost during image analysis. `StrainNet`, on the other hand, was able to learn around much of the noise and accurately predict the longitudinal strain in the tendon, which increased as effort level increased. There was a strong linear relationship between the predicted longitudinal strain and percent MVC (**Fig. 3**; $r = 0.784$, $p = 0.002$), which is comparable to the expected linear relationship between strain and stress for tendon mechanics.

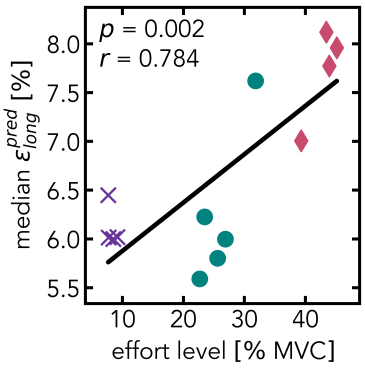


**Figure 3: Median longitudinal strain predicted by `StrainNet` during tendon contraction across all of the trials ($n$ = 13). ×'s, ●'s, and ♦'s correspond to 10% , 30%, and 50% MVC.**

## DISCUSSION

`StrainNet` was able to accurately measure and quantify the different strain levels using ultrasound images of the flexor tendon. For synthetic datasets, `StrainNet` detected subtle differences in deformations with a high degree of accuracy (< 3% error), outperforming existing approaches (*e.g.*, DIC and DDE), which had median strain errors as high as 10%. Additionally, when applied to *in vivo* images, `StrainNet` predicted a strong linear correlation between the measured strain and effort level (percentage of the MVC), further validating the performance of the model. These findings suggest that deep learning models have the potential to significantly advance the accuracy of *in vivo* biomechanics studies.

There are several limitations to our model that will be addressed in future work. First, the model was evaluated on a single tissue type and location, so it is not clear whether it can be applied to a wider range of tissue types. Additionally, the current architecture is specialized to handle only three types of deformation, and it would be useful to explore expanding its capabilities to a wider range of deformations (*e.g.*, shear). Lastly, improvements to the architecture or training the model on a larger dataset may also allow us to remove the need for the first stage of the model, which currently classifies the type of deformation present in the image pair.

The potential applications of `StrainNet` are numerous and exciting. Our results indicate that `StrainNet` greatly outperforms traditional image texture correlation algorithms in controlled settings, such as the synthetic test cases (**Fig. 2**). In more challenging environments where image texture correlation is prone to error due to image artifacts, such as *in vivo* measurements of tendon mechanics in real time, `StrainNet` has demonstrated the ability to provide reasonable and expected levels of tissue deformation (**Fig. 3**). Taken together, these findings suggest that `StrainNet` could be applied to a wide range of biomedical contexts, including *in vivo* studies of muscle function, blood flow, and tissue viability. Overall, the design and capabilities of `StrainNet` are ripe for continued research and development, with the potential for significant advancements in these areas.

The code, trained models, and tutorial for using `StrainNet` will be available at `strainnet.net`.

## ACKNOWLEDGEMENTS

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