A Deep Learning Approach for Stress Analysis of Vertebrae

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Introduction

Biomechanical models have proved their use in surgical planning, but slow computational times prevent them from being used in intraoperative scenarios. In recent works, artificial neural networks (ANNs) have been used to substitute finite element analysis (FEA) at a reduced computational cost [1]. However, this approach has only been demonstrated for relatively simple models, where the simulations vary in only one mode. In this work, the scenario of a vertebra under compression is considered with increasingly complex simulations, evaluating the performance of the FEA-ANN framework at each stage.

Methods

Using an image registration method [2], a topologically consistent set of tetrahedral meshes was constructed from a dataset of 50 segmented lumbar vertebra images [3]. This dataset was subdivided into training, validation and testing sets in a ratio of 3:1:1. Data augmentation methods were used to expand each dataset tenfold by randomly generating new samples.

Three sets of FEA were completed. The first was a vertebral body with uniform material properties, with one face fixed and a distributed force applied to the other; the simulations only varied by the shape of the vertebra. The second set differed by assigning the material properties elementwise using BoneMat [4] to estimate the true Young's Moduli from the original CT scans. The third set introduced two new parameters which linearly scaled the magnitude of the applied force and the young's moduli; these parameters were randomly generated for each simulation.

Using principal component analysis, the dimensionality of the FEA results was reduced from 188289 to 24, 31 and 32 respectively. The mesh coordinates were compressed similarly. For each simulation set, NeurEco was used to train an ANN, taking the compressed mesh coordinates (and, for the third set, the two additional parameters) for its inputs and the compressed FEA results as its outputs. Each network was then evaluated on the testing dataset.

Results & Discussion

The testing dataset results obtained using the ANN and FEA approach showed strong fidelity, yielding mean absolute percentage errors of 10.46%, 11.51% and 11.01% for the respective order of FEA sets. These results show consistent performance, despite the increasing simulation complexity, thus suggesting that the simulation complexity is not yet a limiting factor in this method's performance. Furthermore, for all three simulation sets, the ANN substitute was significantly faster than the original simulation, averaging less than 1% of the execution time.

Conclusions

Although the work here has shown consistency in the testing errors, it should not be assumed that, if the model complexity continued to be increased, it would not eventually become a limiting factor in the ANN performance. Future work should continue to increase the simulation complexity, up to the point of a clinically relevant scenario, and focus on comparing not only the testing set errors, but also the corresponding increase in the network depth and complexity required for an ANN to accurately capture the phenomena.

References

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