Deep Learning Methods and Reduced Order Modelling Techniques for Patient-Specific Spine Models

Confirmation Review Report Summary

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Introduction

Low back pain (LBP) has an estimated lifetime prevalence of 60% - 70% and is recognised by the World Health Organization (WHO) as a 'priority' disease and a major contributor to disability and work absence [1]. LBP can arise as a symptom of a variety of conditions, but intervertebral disc degeneration has been identified as a leading cause of chronic cases [2]. However, surgical interventions in the spine are notoriously challenging, often resulting in revision surgeries; a recent study on the topic of surgical interventions for disc degeneration presented one-year revision rates of 9.75% and 9.69% for discectomy and laminectomy procedures respectively [3].

Finite element analysis (FEA) is well established in the field of biomechanics, but slow computational times and manual setups prevent FEA from being implemented in time-constrained applications. In recent publications, artificial neural networks (ANNs) have been used to substitute finite element analysis (FEA) at a reduced computational cost [4]. However, this approach has thus-far only been applied to simple geometries, where sets of topologically consistent subject-specific meshes can be easily generated by defining the mesh distribution on the geometry's edges. This topological consistency is essential for training the ANN substitute; however, it can pose a challenge in a set of anatomical geometries, where edges are typically not clearly defined.

First Year Activities

Methods

During the first year of work an ANN-substitute was developed for an FEA model of a single lumbar vertebra under a compressive load. The dataset, publicly available from SpineWeb [5], contained 40 lumbar vertebrae (8 spines) which were used for training the model, while 2 more spines were retained for testing.

Before the ANN substitute could be trained, it was necessary to implement the FEA simulation for each of the samples in order to generate a training set of results. The first step in implementing the FEA simulation was to generate a mesh for each subject, however, in order for the results data to be viable for training the ANN, every mesh would need to be topologically consistent (i.e. possess the same mesh connectivity). This was achieved using an image morphing algorithm, adapted from [6]. The algorithm's inputs are segmentations of a reference vertebra (I_0) and a target vertebra (I_1), and outputs are the displacement fields that morph I_0 to I_1. Using a 'typical' L3 vertebra as I_0, the morphing algorithm was applied using each of the other training samples as I_1. Each of the displacement fields obtained from the morphing approach were subsequently applied to a reference mesh of I_0, thus generating 40 topologically consistent subject-specific meshes. Using GetFEM++, all 40 meshes were implemented in FEA simulations under compressive loads.

Using principal component analysis (PCA), the dimensionality of the stress results and the mesh coordinates were reduced from 44,058 to 20 and from 55,095 to 4 respectively. NeurEco, a factory for building ANNs with intricate yet minimal structures, was used to train an ANN for predicting the reduced FEA stress results from the reduced mesh coordinates.

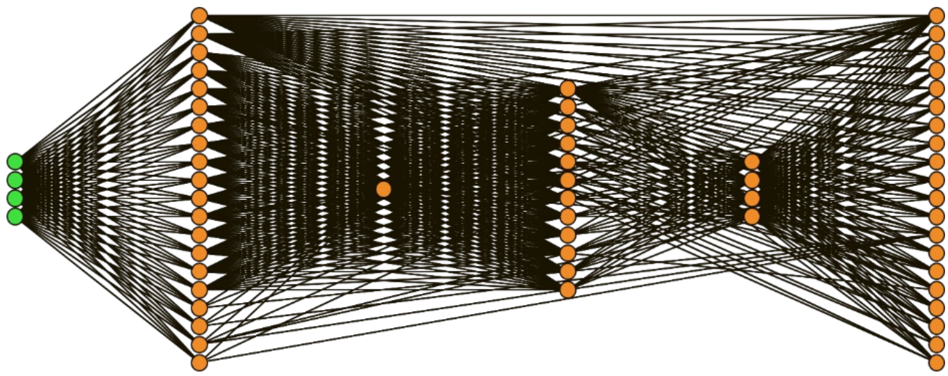

Figure 1) *Depiction of the parsimonious ANN built using NeurEco. There are only 57 nodes and 469 links, arranged in 5 partially connected layers.*

With the ANN-substitute completed, the next step was to evaluate its performance using a new set of 'unseen' data (i.e. data not used during the training of the model.) This testing set consisted of 10 lumbar vertebrae (2 spines), which had previously been retained from the same larger dataset that the 40 training vertebrae had been drawn from. Using the components obtained from the training set (I_0, the ANN, the left singular vectors from PCA), the testing set was evaluated by applying first the morphing algorithm (the testing data was I_1, I_0 must be the same as during the training to preserve mesh topology) then the linear compression, followed by the ANN and finally the linear decompression to reconstruct a prediction of the FEA simulation results. The FEA simulation was applied directly to the testing set to obtain a set of 'true' results to which the ANN prediction could be compared.

Results

The stress results of the testing set obtained from FEA simulation and from the ANN prediction showed excellent fidelity, achieving a mean absolute percentage error (MAPE) of 6.00 % in the Euclidean norm of the output vector. Furthermore, the execution time of the ANN was, on average, only 1.14 % of the execution time of the equivalent FEA simulation.

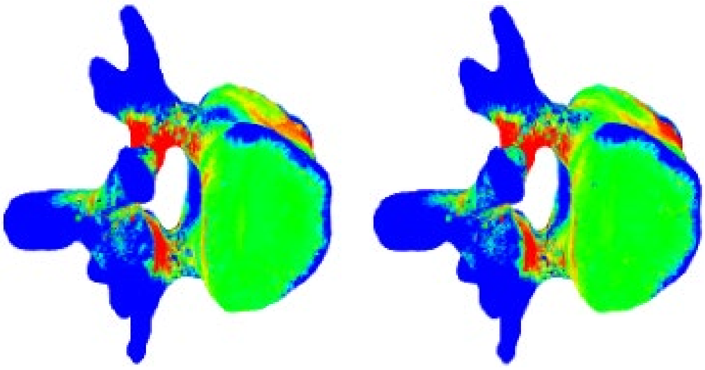

Figure 2) *Results on a testing set vertebra for σ_{11} of the Cauchy stress tensor, obtained using FEA (left) and the ANN (right).*

Plan for the Second and Third Years

The work of the first year has yielded a preliminary study demonstrating the use of a mesh algorithm to enable the "ANN-substituted FEA" approach to be implemented even in the case of complex anatomical geometries. Although the focus of this work has been, and will continue to be, on the spine, the approach is equally applicable to any FEA simulation, thus opening the door for biomechanical simulations to be applied in a variety of severely time-constrained applications. The underlying single vertebra FEA simulation used in the first year was designed as an initial demonstration, focussing on capturing the geometrical variation between subjects; consequently, it was not necessary to take extensive care in designing precise, physiologically representative boundary conditions. One of the next steps in the work will be to replace this initial FEA simulation with a more complex setup that can yield clinically relevant results.

Furthermore, to-date the work on the "ANN-substituted FEA" approach, both in this project and in the literature, has focussed exclusively on using the subjects' shape variation as the basis for the ANN input, without considering any other subject-specific parameters. This presents clear avenue to further develop the approach by incorporating subject-specific boundary conditions (based on patient data such as body weight), or material properties (obtained from medical images using a software such as BoneMat). Finally, alongside the subject-specific parameters, there is the possibility to consider how the subject is augmented during the simulation; in this case, such parameters could describe the surgical treatment, perhaps representing the depth of insertion or orientation of a pedicle screw. If the "ANN-substitute FEA" approach could successfully be implemented with due consideration to all these described parameters, then the resulting ANN would potentially be an extremely useful tool for surgical planning, allowing for rapid evaluation of different surgical parameters in a patient-specific simulation.

References

[1] Duthey, B., (2013). Priority Medicines for Europe and the World A public health approach to innovation. WHO Background paper, 6.24

[2] Mooney, V., (1989). Where is the lumbar pain coming from?. *Annals of medicine*, **21**(5), 373-379.

[3] Kao, F.C., Hsu, Y.C., Wang, C.B., Tu, Y.K. and Liu, P.H., (2018). Short-term and long-term revision rates after lumbar spine discectomy versus laminectomy: a population-based cohort study. *BMJ open*, **8**(7), e021028.

[4] Liang, L., Liu, M., Martin, C. and Sun, W., (2018). A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis. *Journal of The Royal Society Interface*, **15**(138), p.20170844.

[5] SpineWeb, (2013). Datasets [online]. *SpineWeb*. [Viewed 24 July 2019]. Available from: http://spineweb.digitalimaginggroup.ca/spineweb/index.php?n=Main.Datasets

[6] Fehrenbach, J. and Masmoudi, M., (2008). A fast algorithm for image registration. *Comptes Rendus Mathématique*, **346**(9-10), 593-598.