STRESS ANALYSIS OF A VERTEBRA USING ARTIFICIAL NEURAL NETWORKS AND MESH MORPHING

Cameron James (1, 2), Mohamed Masmoudi (1, 3), Kateryna Bastova (1), Lingzhong Guo (2)

1. Adagos, France;
2. Department of Automatic Control and Systems Engineering, The University of Sheffield, UK;
3. Toulouse Mathematics Institute, France;

Introduction

Low back pain is recognized by WHO as a priority condition and a leading cause of disability [1]. Despite this, surgical interventions are notoriously challenging [2] and typically are not considered except in chronic cases where conservative treatment options have failed. Biomechanical models have already proved their use in surgical planning. However, slow computational times and manual setups prevent these models from being implemented as tools in intraoperative scenarios.

Recent developments have demonstrated the use of artificial neural networks (ANNs) to substitute finite element analysis (FEA) at a reduced computational cost [3]. To-date, this approach has only been applied to simple geometries, where the mesh of each subject can easily be made topologically consistent by defining its distribution on the geometry's edges. This topological consistency is essential for training the ANN; however, it can pose a challenge in a set of anatomical geometries, where edges are typically not clearly defined.

As a preliminary study, we will discuss here the construction of an ANN substitute for FEA of a single lumbar vertebra, using a mesh morphing approach to solve the issues of mesh topology.

Methods

The morphing approach was based on the algorithm presented in [4] with an adaptation for a hierarchical multigrid approach. The algorithm's inputs are segmentations of a reference vertebra (I0) and a target vertebra (I1), and outputs are the displacement fields that morph I0 to I1. The dataset [5], contained 40 lumbar vertebrae (8 spines) which were used for training the model, while 2 more spines were retained for testing. Initially, every combination of I0 and I1, using the 40 training vertebrae, were tested to investigate how selecting I0 and I1 from different vertebra levels or subjects would influence the results.

After the initial investigation, a 'typical' L3 vertebra was chosen as I0 for building the ANN and a tetrahedral mesh of I0 was generated using MeshLab. The nodal coordinates of the I0 mesh were combined with the displacement fields obtained from the morphing approach to create a set of 40 meshes. Using GetFEM++ to implement FEA, all 40 were simulated under non-physiological loading. NeurEco, a factory for building ANNs with intricate yet minimal structures, was used to train an ANN for predicting the FEA stress results from the mesh coordinates. The testing set was evaluated using the same approach to build the mesh.

Results

On the training set, morphing I0 achieved a mean Sørensen-Dice coefficient of 0.99 compared to I1. The accuracy of morphing between subjects vs. between vertebra levels was not significantly different ($p=0.46$), nor between both simultaneously vs. just one ($p=0.69$, $p=0.59$ respectively). Thus, the entire training set could be used for the ANN, regardless of level or subject.

In evaluating the testing set (10 vertebrae), the stress results 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.

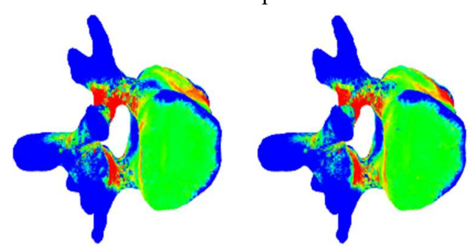

Figure 1: Testing set results for σ_{11} of the Cauchy stress tensor, obtained using FEA (left) and the ANN (right).

Discussion

The morphing approach presented here has allowed the implementation of an ANN substitute for FEA, even in the case of complex anatomical geometries, thus opening the door for biomechanical simulations to be applied in severely time-constrained applications. With the key challenge of obtaining topologically consistent meshes overcome, the approach will be further developed by applying more physiologically relevant loading conditions and by introducing richer subject-specific training data to the ANN, for example: by assigning subject-specific material properties.

References

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