BONE REMODELLING WITH ARTIFICIAL NEURAL NETWORKS

Ana Pais (1), Jorge Lino Alves (2), Jorge Belinha (3)

1. INEGI - Institute of Science and Innovation in Mechanical and Industrial Engineering, Portugal; 2. INEGI, FEUP – Faculty of Engineering, University of Porto, Portugal, Country; 3. ISEP – School of engineering, polytechnic of Porto, Portugal

Introduction

Differences in bone anatomy occur naturally in the population which result in different structural responses. To reduce the computational cost associated with the prediction of the remodelling process, machine learning techniques can be combined with the FEM. It is demonstrated in this work that neural networks achieve accurate solutions in a fraction of the time, with the main disadvantage being the need to collect large amounts of data.

Several approaches to bone remodelling taking advantage of neural networks can be found in the literature, with the work of [1] which predicts the trabecular arrangement from a known load case (direct problem), the work of [2] dealing with the inverse problem and predictive models to adjust the remodelling parameters, leading to more accurate predictions [3].

Materials and methods

In this work, a feed forward neural network (NN) was used. In these networks, each neuron or perceptron *i* does a non-linear transformation, according to (1)

$$z = f(b + wx) = f(b + \sum_{i=1}^{m} w_i x_i) \qquad (1)$$

where f is the activation function, b is the bias, w_i is the weight from the neuron in the previous layer and x_i is the value from the neuron in the previous layer. The training procedure allows to adjust the weights and the bias by minimizing an error function, for example the mean square error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (2)$$

The relevant variables for the problem are shown in Figure 1. The variables α and β evaluate the angles of the two forces being applied, the variables h, l and ϑ are geometry parameters to quantify anatomical differences.

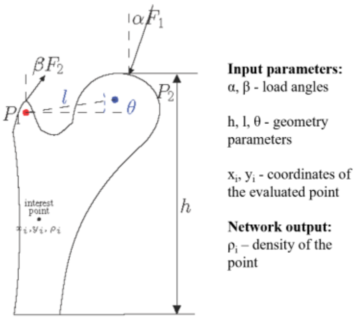

Figure 1 – Problem formulation and relevant variables

The data used to train the network was gathered using bone remodelling analysis and the FEM.
Two different training stages were performed. The first one where the network predicts the density field for a new geometry with a load case which had been seen, consisting of a two-layer network. The second one predicts the density field for a new load case, knowing the geometries from the training. The second network consists of a three-layer network.

Results and discussion

Figure 2**Error! Reference source not found.** shows the output of the three layer network, which is the prediction of the density field for a new load case. The first column refers to the FEM result, the second column is the NN output and the third column quantifies the difference between the two.

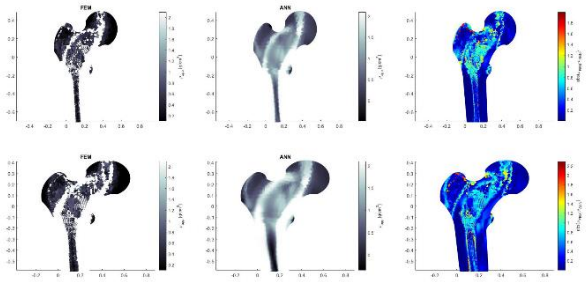

Figure 2 – Neural network results

Qualitatively, the network was able to achieve accurate results in comparison to the FEM result.
In order to provide a valid alternative to the FEM, the prediction time should be lower than the time necessary to run the analysis which can be extensive due to the iterative nature of the process.

Each remodelling analysis took 1020s while a prediction for the same number of points takes about 0.064s. The training procedure also took the equivalent time to run 3.4 FEM analyses.

The main disadvantage of the neural network framework is the amount of data which must be gathered in order to achieve accurate results.

References

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Acknowledgements

The authors truly acknowledge the funding provided by LAETA, under project UIDB/50022/2020 and the doctoral grant SFRH/BD/151362/2021 (FCT, MCTES, State Budget, ESF, Por_Norte) under the MIT Portugal Program.