SCREW LENGTH IMPACT ON BONE STRAIN FOR A PROXIMAL HUMERAL PLATE VIA A NEURAL NETWORK MODEL

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Introduction

Treatment of proximal humeral fractures is challenging and a high rate of failure has been reported when using locking plates [1]. For a given fracture, there are multiple options in terms of the number and length of screws needed to stabilise the fracture and hence it is difficult to capture the mechanics of all possible combinations. FE modelling were used in the past to understand the mechanics of fracture fixation, but due its high computational cost it is not possible to study all configurations. Therefore, the purpose of this study is to use a combination of FE analysis and surrogate modelling to analyse humeral bone strain as screws length are varied.

Methods

A CT image of a cadaver from the New Mexico Decedent Image Database (NMDID) was used to generate a FE model of a proximal humerus [2], in which a single fracture was simulated. A fracture plate with seven proximal screws and three distal screws was implanted. Non-homogeneous material properties were defined [3], tied conditions were set between the screws and the bone and an axial bending loading condition was simulated [4]. In order to vary the length of the seven proximal screws, four values of tip-to-joint distance (TJD) were introduced, defined as the distance between the tip of the screws and the bone surface [5], and training sets of 50, 100, 200, 500 and 1000 FE models were generated using the latin hypercube sampling method. A further set of 100 FE models was generated to test the network, once developed. All the models were run in Abaqus. The TJD of each screw and the strain in the humeral head were used as input and output for the generation of different Neural Networks (NN). The NN outputs were compared with the results from the FE analysis, showing R^2, slope and RMSE for the 100 unseen cases. Differences between single and multiple-output NN were shown, using the bone strain around each screw as output. To further test the quality of the NN, a set of 30 models was developed with additional intermediate values of TJD, and the output from the FE simulations was compared with the predictions of the NN. To understand the impact of the screws' length in the humeral head, the best NNs were used to make a simulation of all 4^7 possible configurations.

Results

The NN predictions of principal strain around the proximal screws were compared with the FE results of the 100 unseen data, showing a good correlation and a low level of error (R^2 = 0.99, RMSE = 21.1-62.7 µstrain). Single and multiple-output NNs gave comparable results, with the same R^2 and range of error (R^2 = 0.96-0.99, RMSE =24.6-148.1 µstrain). Once the NN was tested with intermediate values of TJD, a higher level of error was observed (RMSE = 28.7-1190.7 µstrain). Predictions of all configurations made with NNs showed that the screw providing medial support is the most influential on the bone strain, and the safest configuration is the one with longer screws. (Figure 1)

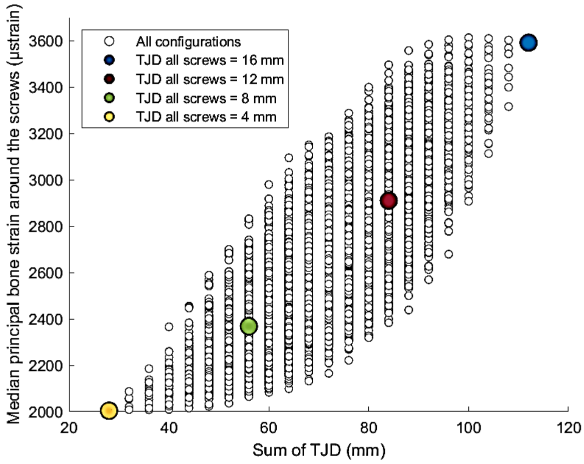

Figure 1 - Variation of the median principal bone strain for all configurations with the variation of the sum of the TJD of all the screws. Focus on the configurations in which all the proximal screws have the same TJD.

Discussion

The aim of this study was to develop a Neural Network method to reproduce the bone strain varying the length of the screws of a fracture fixation plate implanted in the proximal humerus. The NN was able to give an accurate prediction of strain and compute the entire solution space, not feasible using FE alone. This technique can be used in the future to understand the influence of additional parameters.

References

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