

**Marie Skłodowska-Curie Actions (MSCA)
Innovative Training Networks (ITN)
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spinner
next generation spine experts

**SPINe: Numerical and Experimental Repair Strategies
Management Meeting
Friday, 23rd October 2020**



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Management Meeting
Friday 23rd October 2020



The
University
Of
Sheffield.



A Deep Learning Approach to Biomechanical Simulation of the Lumbar Spine

ESR6: Cameron James



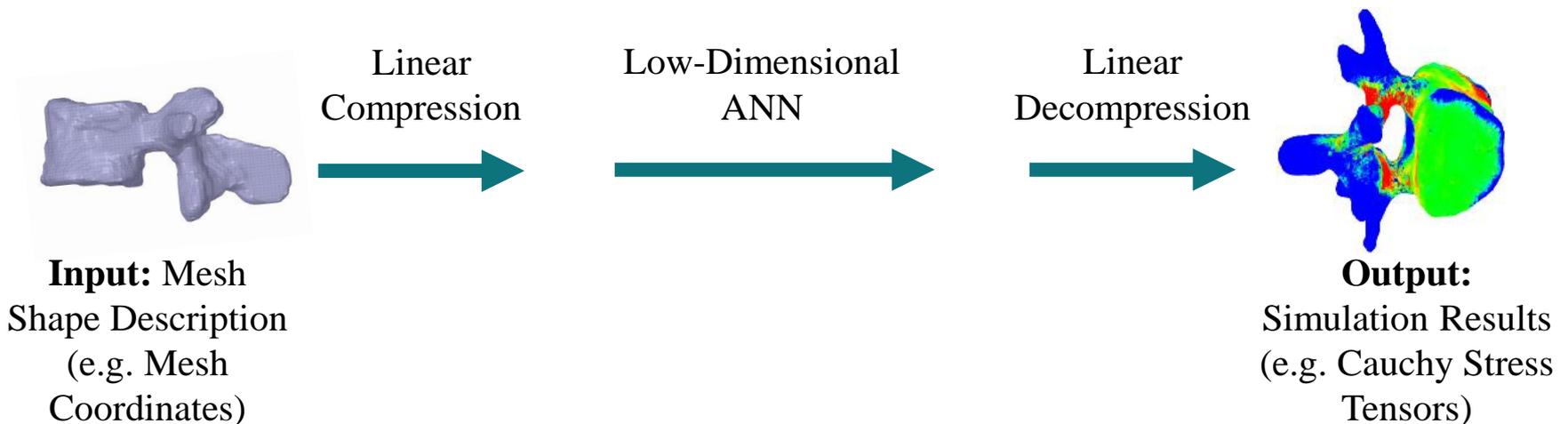
Project Aim

“ To develop real-time biomechanical simulations of spinal surgical setups by integrating parsimonious deep learning approaches into the setup and execution of finite element simulations. ”



An ANN-Based Emulator

- Training data is generated by running finite element simulations with slightly different setups (e.g. subject specific spine geometries)
- An artificial neural network (ANN) is trained to predict the simulation results from the setup parameters (e.g. mesh coordinates describes the subject specific geometry)
- The completed ANN can then be exploited to rapidly predict the simulation results for new samples, without the need to setup or run a finite element simulation.





Current Objectives

- 1) Mesh Morphing for Anatomical Shape Parameterisation
- 2) Inputs Describing Multiple Classes of Subject-Specific Variations

Future Objectives

- 1) Apply Methods to a Clinically Relevant Scenario



Objective 1 : Mesh Morphing for Anatomical Shape Parameterisation

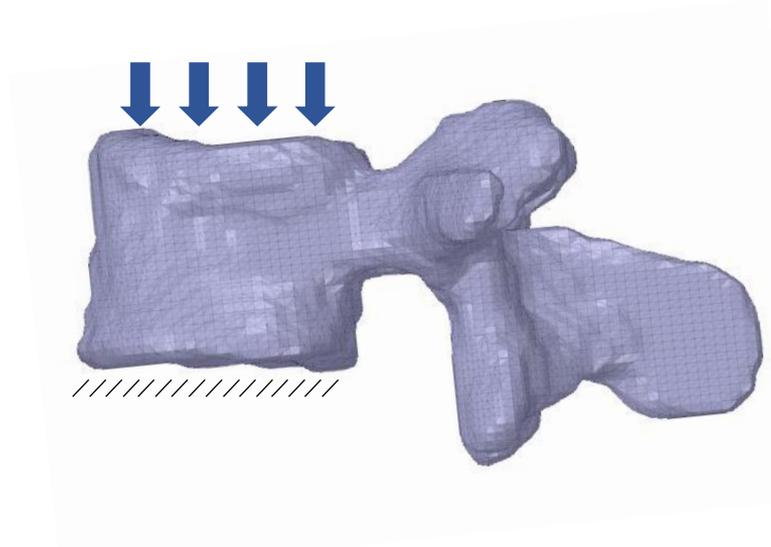
Objective : “ By using a mesh morphing approach to parameterise the shape variations in a training set of lumbar vertebra, develop an ANN to substitute the simulation of a lumbar vertebra under a compressive load. ”

Dataset (Yao *et al.*, 2012) :

- ▶ CT scans with manual segmentations
- ▶ 10 spines (50 lumbar vertebrae)
- ▶ Fully anonymised and publicly available at:

SpineWeb.DigitalImagingGroup.ca

The Simulation :





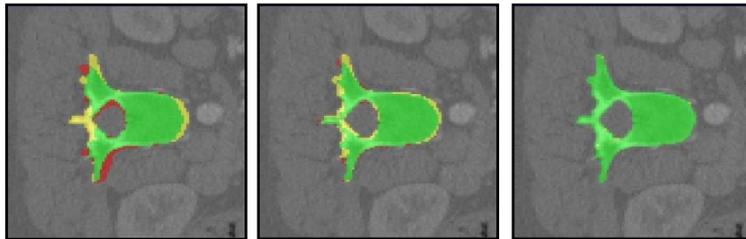
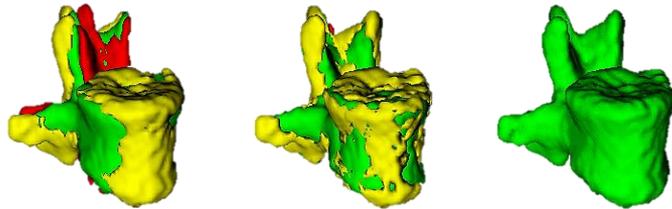
Mesh Morphing

Initial Positions

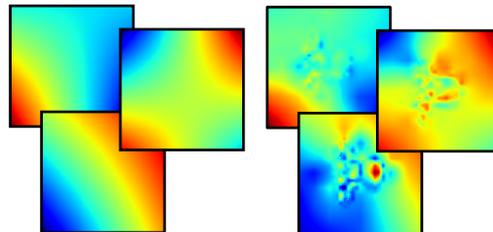
1st Iteration
Grid Size 128

Final (7th)
Iteration
Grid Size 4

Morphing Results



V_x, V_y & V_z



Morphing Results Key :

		Morphed I ₀	
		T _{true}	F _{alse}
I ₁	T _{true}		
	F _{alse}		

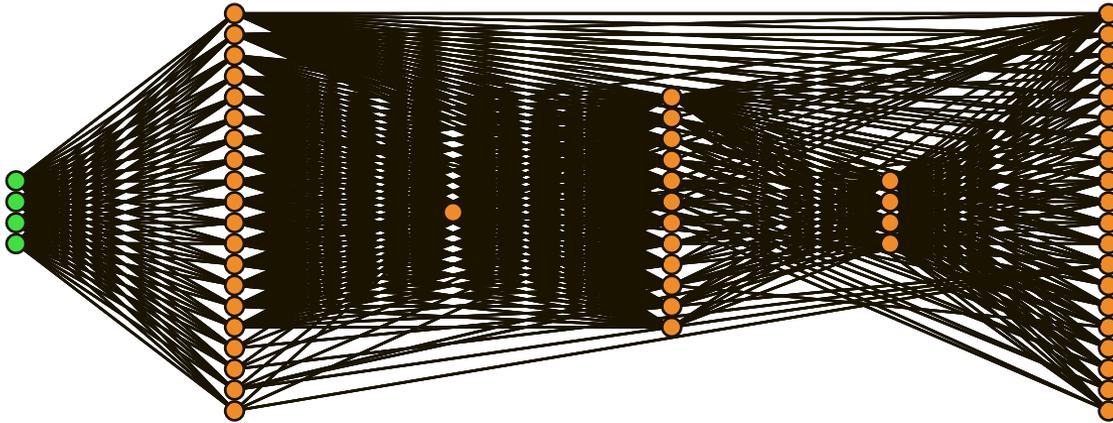
Metrics

- ▶ Dice Similarity Coefficients:
 - ▶ 0.999 ± 0.002
- ▶ Significance Tests for Variation Modes:
 - ▶ Inter-subject vs. Inter-level :
p = 0.46
 - ▶ Inter-subject vs. Inter-Subject & Inter-level simultaneously :
p = 0.69
 - ▶ Inter-level vs. Inter-Subject & Inter-level simultaneously :
p = 0.59



Training the ANN

- ANN Trained using NeurEco
- **Inputs** : Mesh coordinates, linearly compressed to reduced dimensionality from 55095 to 4.
- **Outputs** : Corresponding simulation results in the form of Cauchy stress tensors, linearly compressed to reduced the dimensionality from 44058 to 20.

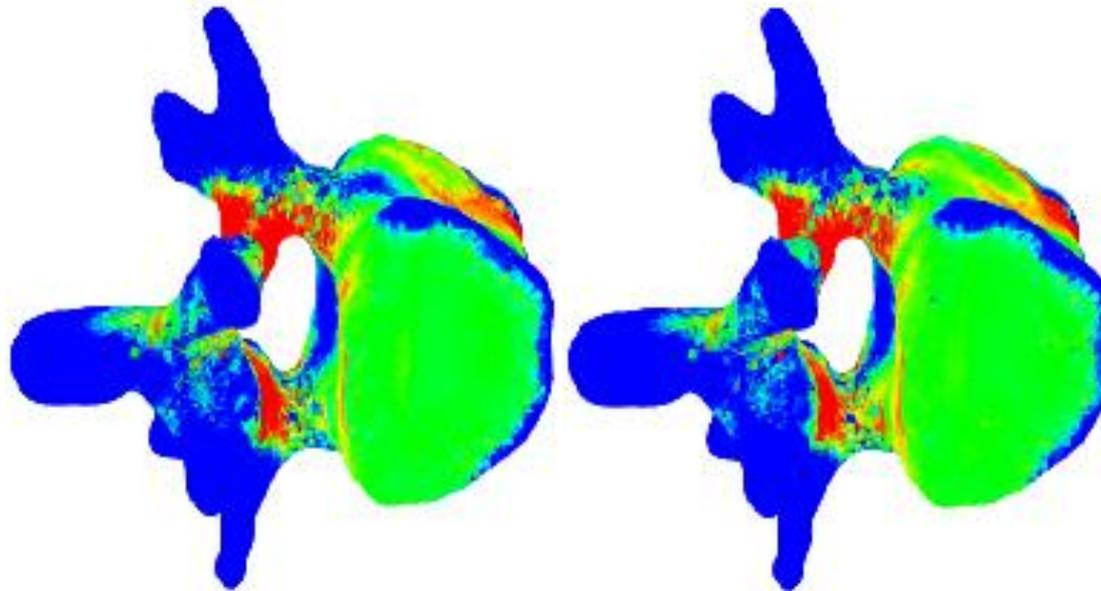


- ▶ **Number of Nodes** : 57
- ▶ **Number of Links** : 469
- ▶ **Number of Layers** : 5 (*Partially Connected*)



Results

Testing Sample Results for σ_{11} of the Cauchy stress tensor



**Finite Element
Simulation**

Neural Network

- **MAPE of 6.00 % in the Euclidean norm of the output vector.**
- **Execution time of the ANN was, on average, around 1% of the execution time of the equivalent FEA simulation.**

Objective 2 : Inputs Describing Multiple Classes of Subject-Specific Variations

Objective : “ Developing on the previous work in shape parameterisation, increase the variability within the set of training simulations by incorporating subject-specific material properties and variable loading conditions. ”



Material Properties & Forces

Material Properties

- Assigned elementwise using BoneMat
- Density-Elasticity Relationship drawn from (Morgan *et al.*, 2003)
- No Phantom for calibrating Hounsfield-Density Relationship – instead, calibration coefficients were designed based on the expected range of density values
- Each geometric sample was implemented for 36 sets of calibration coefficients - expanding the training set from 40 samples to 1440 samples.

Forces

- Boundary condition were kept exactly the same, with the exception of the magnitude of the compressive force
- Each sample was simulated under 3 different magnitudes



Training the ANN

Ongoing...



Conclusions & Plans

1. Shape parameterisation using mesh morphing has been successfully used to create a set of simulated training data – leading to a simple ANN-based simulation of a vertebrae under compression.
2. Work on “Objective 2” still needs to be completed
3. Current work has focused mainly on addressing challenges for the methodology – however, the work will have to eventually be demonstrated in the context of a clinical scenario.



Acknowledgements



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