A Coupled Shape Model of the Torso and Upper Limb Bones

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Summary

A coupled statistical shape model that captures the morphology of the torso (ribcage and sternum) and upper limb bones (clavicle, scapula, humerus, radius and ulna) was developed to improve scaling of musculoskeletal models. A Partial Linear Square Regression model predicted bone morphology from age, sex, mass, height and linear measurements (clavicle length, scapula length, scapula width, humerus length, humerus epicondyle width, torso width, torso depth, torso length and sternum length). Leave-One-Out analysis showed that the model predicted bone geometry with root mean square errors of ~6.5mm. Our model provides a useful tool to scale the torso and upper limb bones for biomechanical simulation.

Introduction

The human upper limb displays a large range of motion thanks to the kinematic coupling between the trunk, clavicle, scapula and humerus. This functional interdependence is likely to be present in the morphological form of the upper limb bones. Statistical shape models efficiently and accurately capture variations in anatomy [1] and have been used to investigate bone morphology of the scapula and humerus [2]. Here we developed and validated a coupled shape model of the upper limbs, including the torso (ribcage and sternum). We explored how this model can predict bone morphology using simple demographics and linear bone measurements, providing a new scaling tool for upper limb modelling.

Methods

A shape modelling pipeline (GIAS3, [3]) was used to create a coupled shape model of the torso, clavicles, scapulae, humeri, radii and ulnae from 48 segmented CT scans. Principal Component Analysis (PCA) captured the morphological variation (shape and size) across the population. Principal component weights were used to train a Partial Least Squares Regression to predict bone geometry using demographics (age, mass, height and sex) and linear bone measurements from anatomical landmarks (Figure 1). Root mean square error (RMSE, mm) between the predicted bone geometry and segmented CT data was quantified and we measured the predictive performance of the regression model using a Leave-One-Out analysis.



Figure 1: Landmarks used for anthropometric measurements

Results and Discussion

The first 13 principal components accounted for 90% of the variation in bone morphology across the population. The mean fitting RMSE was 0.68 ± 0.1 mm for upper limb bones and 0.97 ± 0.4 mm for the torso. Bone morphology prediction after a leave-one-out results in an average RMSE of ~6.5mm (Figure 2). Variations in torso shape gave rise to the largest prediction errors. The shape model of the upper limb bones and torso was split into two models to investigate this variation. Predicted upper limb bones gave an average RMSE of ~3.5mm, and predicted torsos gave an average RMSE of ~8.0mm. Errors in the upper limb bones were influenced by handedness, which was not considered in the training dataset. However, coupling the upper limb bones with the torso improved the bone morphology prediction.

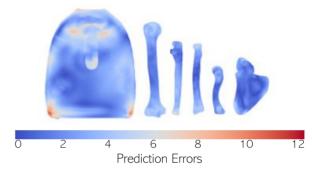


Figure 2: Mesh-to-mesh comparison of predicted upper limb bones compared to ground-truth segmented CT scans.

Conclusions

We developed a coupled shape model of the torso and upper limbs and showed that using PLSR, with demographics and linear bone measurements as input, we could predict torso and upper limb morphology to within ~6.5mm. This model can be clinically useful for estimating bone morphology when presented with sparse data.

Acknowledgements

We thank the NZ Ministry of Business, Innovation and Employment (MBIE) for financial support and the Victorian Institute of Forensic Medicine (VIFM) for the CT scans. We also thank Eric Shen for helping with segmentation.

References

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