Leveraging Graph Neural Networks for Accurate Foot Deformation Prediction

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Summary

Predicting foot deformation during ground contact is crucial for biomechanics applications such as footwear design and gait analysis. In this study, we employ a graph neural network (GNN) model based on the MeshGraphNet architecture to forecast foot deformation using a custom dataset from Abaqus simulations. By retaining unnormalized node positions and modifying the network architecture, our approach captures variations in foot scale and achieves notable gains in predictive accuracy.

Introduction

Foot deformation prediction is challenging due to the complex biomechanics and inherent variability of human feet. Most existing mesh datasets focus on uniform objects or scaled versions of a single model, often requiring separate models for different cases. In contrast, our dataset comprises only foot models that reflect subtle variations in size and shape. Although MeshGraphNet [1] has been effective for modeling physical systems, its direct application to foot deformation is hindered by data variability. To address this, we extend MeshGraphNet by using unnormalized node data, enabling a single network to generalize across diverse foot models.

Methods

We recruited 100 subjects (57 males, 43 females) aged 20–59 years and collected 186 foot samples (207–285 mm), with 36 randomly selected for testing. A total of 186 foot videos (94 left, 92 right) were captured, and 3D foot models were reconstructed from 2D images using MetaShape and Fusion 360. The models were truncated from the sole to 80 mm above and meshed with approximately 11,789 elements and 18,119 nodes. Finite element analysis in ABAQUS 2020 simulated foot deformation by modeling the foot as a homogeneous, linear elastic material and the platform as a rigid body displaced upward by 10 mm with a 1 mm initial gap. Each simulation produced a 3D mesh (graph) with edge attributes and target deformation values. We then used a modified version of MeshGraphNet to predict the deformation of the foot graph, retaining unnormalized node positions to preserve scale information and adjusting processor layers and hidden dimensions to better suit our data. Predicted deformations were compared to ground truth using the L1 loss function. Training was performed with the Adam optimizer (initial learning rate = 0.001) for 300 epochs (batch size = 4) and evaluated using RMSE, MSE, and MAE.

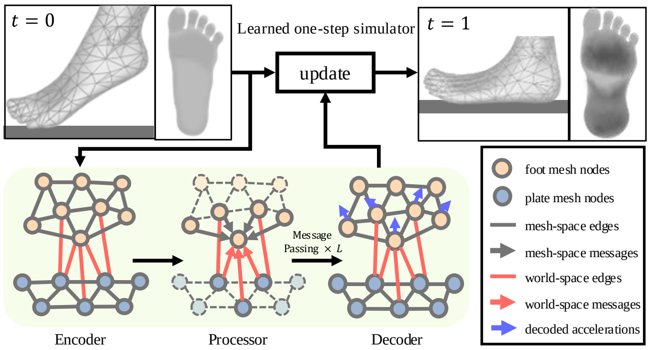

Figure 1: Our scheme using dynamic Graph Neural Networks.

Results and Discussion

Table 1 presents the overall experimental results. "Baseline" corresponds to the scenario in which no deformation is predicted (*i.e.*, the input remains unchanged). "GNN (default)" shows the predictions using the standard settings of MeshGraphNet, whereas "GNN (modified)" reflects the results obtained using our modified approach. The second through sixth columns provide a detailed comparison of configurations: the normalization method, number of encoder layers, processor (message passing) layers, decoder layers, and the hidden layer dimensionality. We observed that the default GNN can capture the majority of the deformation – for example, it achieved an 84.2% improvement in MAE ($3.9003 \rightarrow 0.6173$). Furthermore, our modified GNN further improved prediction accuracy by an additional 3.0% in MAE ($0.6173 \rightarrow 0.4976$). In addition to MAE, we also noted significant improvements in other metrics.

Conclusions

In conclusion, we have developed a GNN-based model specifically tailored to predict foot deformation in datasets with significant scale variability. By retaining the unnormalized node positions and modifying the network architecture, our approach enhances predictive accuracy.

Acknowledgments

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References

[1] T. Pfaff et al. (2021). *ICLR*.

Table 1: Comparison of deformation prediction performance. The values in parentheses represent the relative error percentages.

Method	Norm.	Enc.	Proc.	Dec.	Dim.	RMSE (↓)	MSE (↓)	MAE (↓)
Baseline	–	–	–	–	–	5.8619 (100.0)	34.3613 (100.0)	3.9003 (100.0)
GNN (default)	stand.	1	15	1	128	1.4293 (24.4)	2.0429 (5.9)	0.6173 (15.8)
GNN (modified)	none	1	25	1	64	**1.2136** (20.7)	**1.4729** (4.3)	**0.4976** (12.8)