

PREDICTING ANKLE STIFFNESS DURING CONTROLLED PLANTARFLEXION WITH A CNN-LSTM

Diogo Rijo, João Gouveia, Rui Coelho e Jorge Martins

IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Portugal

[/diogo.rijo, joao.g.gouveia, rui.coelho, jorgemartins}@tecnico.ulisboa.pt](mailto:{diogo.rijo, joao.g.gouveia, rui.coelho, jorgemartins}@tecnico.ulisboa.pt)

KEY-WORDS: Walking Gait, Stance, Ankle Stiffness, CNN-LSTM.

1 INTRODUCTION

In the past decade, the integration of AI in systems like ankle foot orthoses (AFOs) has advanced rehabilitation possibilities for patients with motor impairments. This research presents a study focused on characterizing ankle impedance and developing a CNN-LSTM [1] predictor for joint stiffness at the initial instants after heel strike (HS). Initial findings suggest that optimal ankle impedance linearization occurs between 4% and 6% of the stance phase, yielding an average 92% variance accounted for (VAF) using a least-squares linear regression identification model. Subsequent results indicate an average root mean squared error (RMSE) of 0.78Nm/rad/kg, resulting in a relative root mean square error (rRMSE) of 39% for the predictor's performance, as evaluated using a 10-fold cross-validation method. Additionally, the study also uncovers that the transition from controlled plantar flexion to dorsiflexion occurs before foot flat (FF).

2 EXPERIMENTAL PROCEDURE

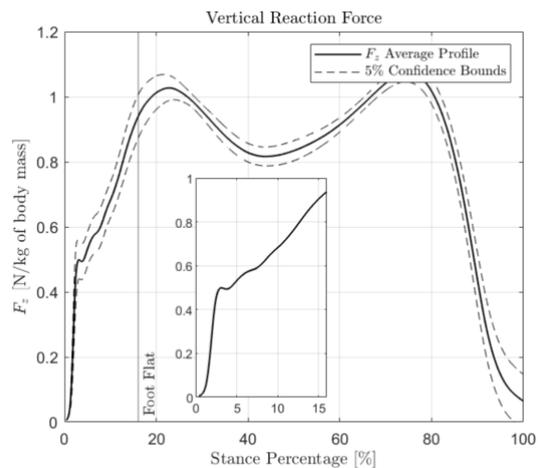
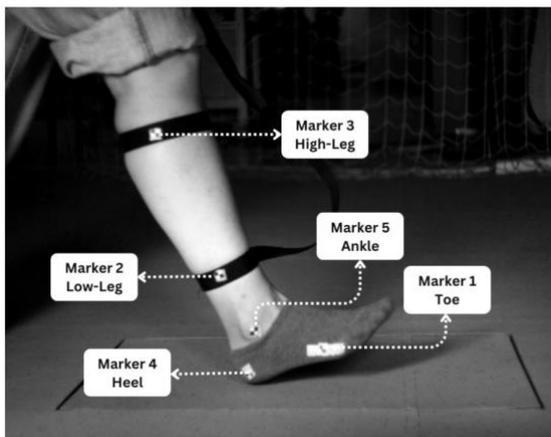


Figure 1 – Left: Experimental set-up. Right: Vertical Ground Reaction Force.

Subjects were instrumented with five position markers in the regions of interest on the foot and leg, Figure 1, as well as an IMU on the dorsal part of the foot (not shown in the figure). The markers were attached to the subject using adhesive tape and adjustment straps. The three foot markers were attached directly to the lateral side of the right foot: one to the ankle area, one to the heel, and one to the area just before the toe joint. The leg markers were attached to two adjusting straps tightened in the area between the knee and ankle. The trajectories of the markers

were extracted using the software Kinovea, providing the ankle angle, and together with the calibrated data of the force plate provided a synchronized estimate for the ankle torque.

3 RESULTS

CNN-LSTM, or Convolutional Neural Network - Long Short-Term Memory, is a type of neural network architecture that combines two powerful deep learning techniques: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. By uniting the two types of neural networks, CNN-LSTMs are particularly useful for tasks that involve sequences of data and require the model to capture both spatial features and temporal dependencies. In the current case, we are looking for the causality between the inertial data of the previous swing phase (obtained from an IMU), to the ankle stiffness at heel strike of the current stance phase.

After the hyperparameter optimization, the model with the best performance achieved an average RMSE for a 10-fold cross-validation of 0.85Nm/rad/kg for the personalized dataset and 0.93Nm/rad/kg for the multi-subject personalized dataset, which corresponds to an average RMSE value of 42% and 45%, respectively. These values, although low, reveal the potential of the approach considering the small size of the training data set.

Table 1 – Hyperparameter tuning.

| Personalized dataset | | | | | Multi-subject dataset | | | | |
|----------------------|------------|------------|--------------|------|-----------------------|------------|------------|--------------|------|
| N_{filt} | L_{filt} | L_{pool} | N_{hidden} | RMSE | N_{filt} | L_{filt} | L_{pool} | N_{hidden} | RMSE |
| 16 | 5 | 10 | 32 | 0.85 | 16 | 5 | 10 | 32 | 0.93 |
| 16 | 5 | 15 | 16 | 0.85 | 16 | 10 | 10 | 16 | 0.94 |
| 16 | 10 | 5 | 16 | 0.85 | 16 | 5 | 5 | 16 | 0.95 |
| 16 | 5 | 10 | 16 | 0.86 | 32 | 5 | 15 | 16 | 0.96 |
| 16 | 15 | 5 | 16 | 0.86 | 16 | 5 | 5 | 64 | 0.97 |

5 CONCLUSIONS

This study advances our current knowledge about human locomotion, enriching the current description of the gait cycle and gait determinants and increasing our understanding of how ankle impedance evolves during the early stance phase. Furthermore, an AI CNN-LSTM joint stiffness prediction model that may find use in AFOs and other walking aid technologies is developed [2]. As shown, the accuracy of the predictor was impacted by the small amount of training data in our early results, which calls for our continued ongoing research.

ACKNOWLEDGMENTS

The authors acknowledge Fundação para a Ciência e a Tecnologia (FCT) for its financial support via the projects LAETA Base Funding (DOI: 10.54499/UIDB/50022/2020) and ReflexES (DOI: 10.54499/2022.04834.PTDC). João Gouveia acknowledges support by FCT through the PhD scholarship 2021.06844.BD.

REFERENCES

- [1] R. M. Coelho, J. Gouveia, M. A. Botto, H. I. Krebs and J. Martins, "Real-time walking gait terrain classification from foot-mounted inertial measurement unit using convolutional long short-term memory neural network", *Expert Systems with Applications*, 203:117306, oct 2022.
- [2] R. M. Coelho, S. Durand, J. Martins and H. I. Krebs, "Multivariable passive ankle impedance in stroke patients: A preliminary study", *Journal of Biomechanics*, 130:110829, 2022.