Inertial measurement unit-based joint angle: a novel deep learning approach based on marker position prediction

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Summary

As we advance in using inertial measurement units (IMUs) for motion analysis, we find ourselves unable to apply the decades of research-based calculations derived for optical motion capture (OMC). This necessitates the development of a novel approach to bridge the gap between IMUs and OMC systems. Hence, we propose an innovative deep-learning approach to predict marker positions using IMU data as an intermediate step in estimating joint kinematics.

Introduction

Recently, IMUs have offered a promising alternative for real-world monitoring [1]. Our previous work developed a model that predicts joint kinematics at various speeds from IMUs [1]. Yet, two concerns persist. First, movement visualization, which could aid the user in gaining confidence in the model outputs, was impossible. Second, predicting joint kinematics directly does not allow the use of computational methods based on positional data that have been rigorously validated.

Methods

Eighteen participants performed walking, jogging, and running trials of 2 minutes on a treadmill while fitted with 7 Xsens IMU sensors (Movella, Netherlands) and retro-reflective markers. Only walking data was used for this study. Each trial was segmented into normalized gait cycles (101 frames). The model predicted 16 marker positions using acceleration and gyroscope data of the 7 sensors. An autoencoder network with multiple long short-term memory, convolutional, and attention layers was validated through a leave-one-subject-out method with an early stopping mechanism. The model was trained using a novel Biomech loss function. Performance was assessed via the root mean squared error (RMSE). After predicting marker positions, the BiomechZoo toolbox [2] was used to calculate joint angles in the sagittal plane according to the Plug-in Gait model [3]from true (OMC) and predicted (IMU) marker positions. Joint angles were compared with and without aligning with dynamic time warping (DTW). In addition, models were also tested on an external database where participants walked on a treadmill at preferred speeds [4].

Results and Discussion

Our model demonstrates an RMSE of 2–5 cm for marker position predictions on our data. For sagittal plane angles across all three joints in our data, RMSE values ranged between 4-7° without DTW and 2-4° after alignment by DTW (Table 1). Our model's performance on the Warmerdam et al. data showed similar RMSE (4-7° without DTW and 2-4° with DTW) values as our initial validation (Table 1).

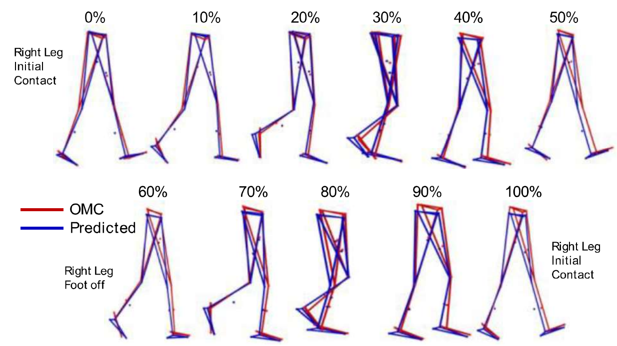

Figure 1: Visual representation of a random walking stick figure from 0-100% of the gait cycle.

Conclusions

This research presents a new method for estimating joint kinematics using IMUs, combining traditional biomechanical models with modern wearable technology. Our approach could be expanded to other IMU positions and other marker configurations.

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References

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Table 1. Joint angle comparison based on optical motion capture (OMC) and predicted marker position using our proposed method

Datasets	Joints	Right Hip	Right Knee	Right Ankle	Left Hip	Left Knee	Left Ankle
Same dataset	Non-DTW	5.2 ± 1.4	5.8 ± 1.3	6.8 ± 2.5	4.5 ± 1.7	5.3 ± 2.2	5.4 ± 2.1
	DTW	2.8 ± 1.2	2.3 ± 0.8	4.0 ± 1.9	1.8 ± 0.7	2.6 ± 1.1	2.1 ± 1.0
External Treadmill [4]	Non-DTW	4.5 ± 1.5	7.6 ± 2.2	6.4 ± 1.9	4.0 ± 1.2	5.0 ± 1.4	5.4 ± 1.9
	DTW	2.1 ± 0.7	3.2 ± 1.1	2.8 ± 1.4	2.1 ± 0.8	2.2 ± 0.8	2.0 ± 0.8

All values represent root mean squared error (RMSE) in degrees. DTW = Dynamic time warping was used to align the data, Non-DTW = no alignment of data. All values in degrees.