A MACHINE LEARNING APPROACH FOR DETERMINING WHOLE BODY ANGULAR MOMENTUM FROM WEARABLE SENSORS

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Introduction
Whole Body Angular Momentum (WBAM) is a useful metric to measure a person's stability during locomotion [1]. However, it is typically calculated from motion capture data, which limits its use to laboratory settings. Additionally, the need for post hoc processing of inverse kinematics inhibits the real-time use of WBAM as biofeedback. Machine learning techniques could be used to estimate WBAM from wearable sensors rather than marker data, enabling mobile collection and real-time use. In this study, we aimed to investigate how well a simple machine learning model could estimate WBAM from wearable sensors on the participant's lower limbs.

Methods
One participant walked at 1.25 m/s on a treadmill embedded in a six degree-of-freedom moving platform (CAREN, Motek Medical, Netherlands). We applied 288 perturbations that varied in magnitude, direction, and timing, providing a diverse data set for creating a machine learning model. We collected data from a full body marker set and six six-axis inertial measurement units (IMUs) positioned on the shank, thigh, and pelvis segments (Fig. 1, A). We calculated frontal WBAM using OpenSim and custom scripts.

Using an initial sliding window length of 250 ms, we performed feature extraction on the sensor data for six features [2]. Our approach used a linear regressor. We began optimizing the model using forward feature selection to determine which of the 36 sensor locations and channels created the most accurate model. Then, we used the same process to optimize the feature type. Lastly, we performed window size optimization on the chosen feature set. We used five-fold validation at each level of optimization (Fig. 1, B). Root Mean Squared Error (RMSE) was used to determine the accuracy of the models' estimations.

Results and Discussion
The final optimized model used 16 of the 36 sensor channels, all 6 feature types, and a window size of 250 ms. Of the sensor channels selected, all six gyroscopes in the z-direction were used in this model, which was expected because they are most aligned with the frontal plane rotation of the segments. The optimized model had an RMSE of 11% of the average steady state peak to peak WBAM and an R^2 value of 0.909 (Fig. 1, C).

The optimized model tracks steady state well, however, when a disturbance to WBAM is caused by a perturbation, the model drifts outside the average RMSE. Due to the cyclic nature of steady state WBAM, the model may depend more heavily on data earlier in the sliding window which may not represent the perturbed WBAM values being estimated. Another possibility is an imbalance in the training set between steady state and perturbed data, which can skew the model towards the more represented data type. Additionally, we did not collect data from the arms, which could also explain the inability to accurately predict WBAM during a perturbation. Overall, the linear regression model was able to estimate WBAM with an average accuracy of 89%, but a more complex model may be more successful at tracking WBAM during a perturbation.

Significance
Tracking of WBAM using IMUs could provide a valuable source of real-time feedback to inform exoskeleton control or biofeedback-based interventions for augmenting biomechanical stability. Future work will include estimates for sagittal and transverse WBAM as well as examine more complex machine learning models, such as a Gaussian regressions or neural networks. Long-term, we aim to apply wearable sensor-based WBAM estimation to track and modulate locomotor stability beyond the confines of the lab.

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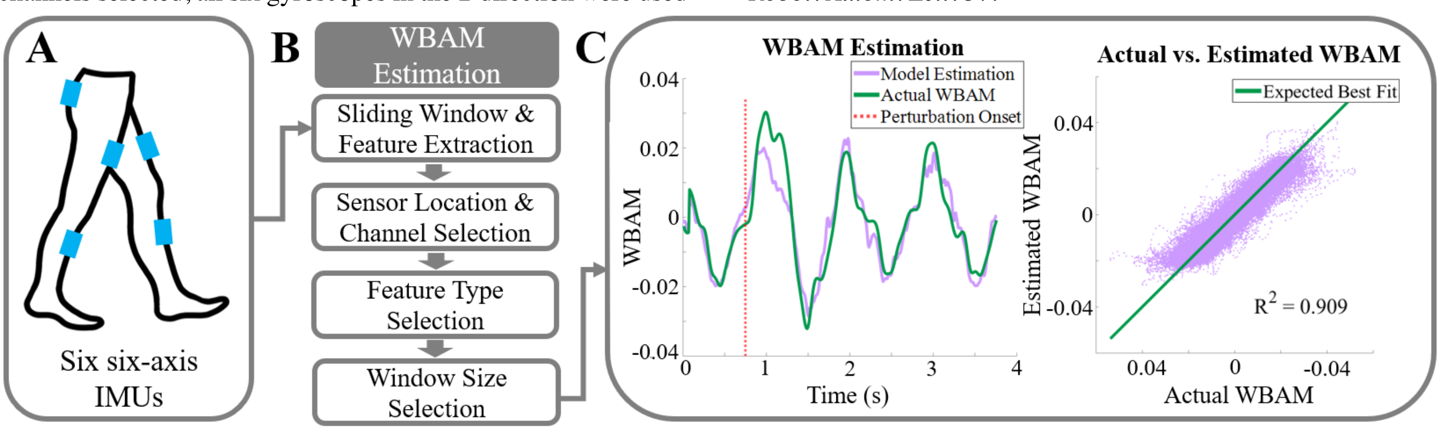

Figure 1: (A) We placed IMUs(blue) on the subject's lower limbs. (B) The optimization methods are demonstrated in a flow chart. (C) A time series graph of Actual and Estimated WBAM with an indicated perturbation onset is shown on the left. The correlation graph of Actual and Estimated WBAM is shown on the right where the expected best fit line is plotted in green.