

Introduction

Ground reaction forces (GRFs) are key to analyzing gait, injury risk, and performance, but are typically measured using lab based systems (force plates, instrumented treadmills) with limited real world applicability. Wearable pressure insoles offer a portable alternative, but suffer from sensor non-linearity, drift, and saturation under high loads. This project uses deep learning and targeted sensor masking to improve GRF estimation from insole data.

Methods

Data Collection

- 128-sensor pressure insole (16×8, 200 Hz)
- Instrumented treadmill for GRFs (2000 Hz)
- Motion capture for lower limb kinematics
- All systems synchronized for timing alignment

Signal Processing

- GRFs downsampled to 200 Hz
- Low-pass Butterworth filter (10 Hz)
- Gait cycles segmented via vertical GRF threshold
- Normalization:
 - GRF → body weight
 - CoP → insole geometry

Model Framework

- Input: 2D pressure maps (8×16)
- Output: Vertical GRF + CoP (ML/AP)
- Model: ViT-Trans3 (num_heads=8, embedded_dim=64)
 - Learning rate 0.0005
 - Batch size 32
 - Train set: DB1(1-7)
 - Val set: DB1(8) ⇒ Test on each subject of DB2-1, DB2-2
- *Model is not perfectly optimized for testing on DB2, just for checking trend of DB2 subjects

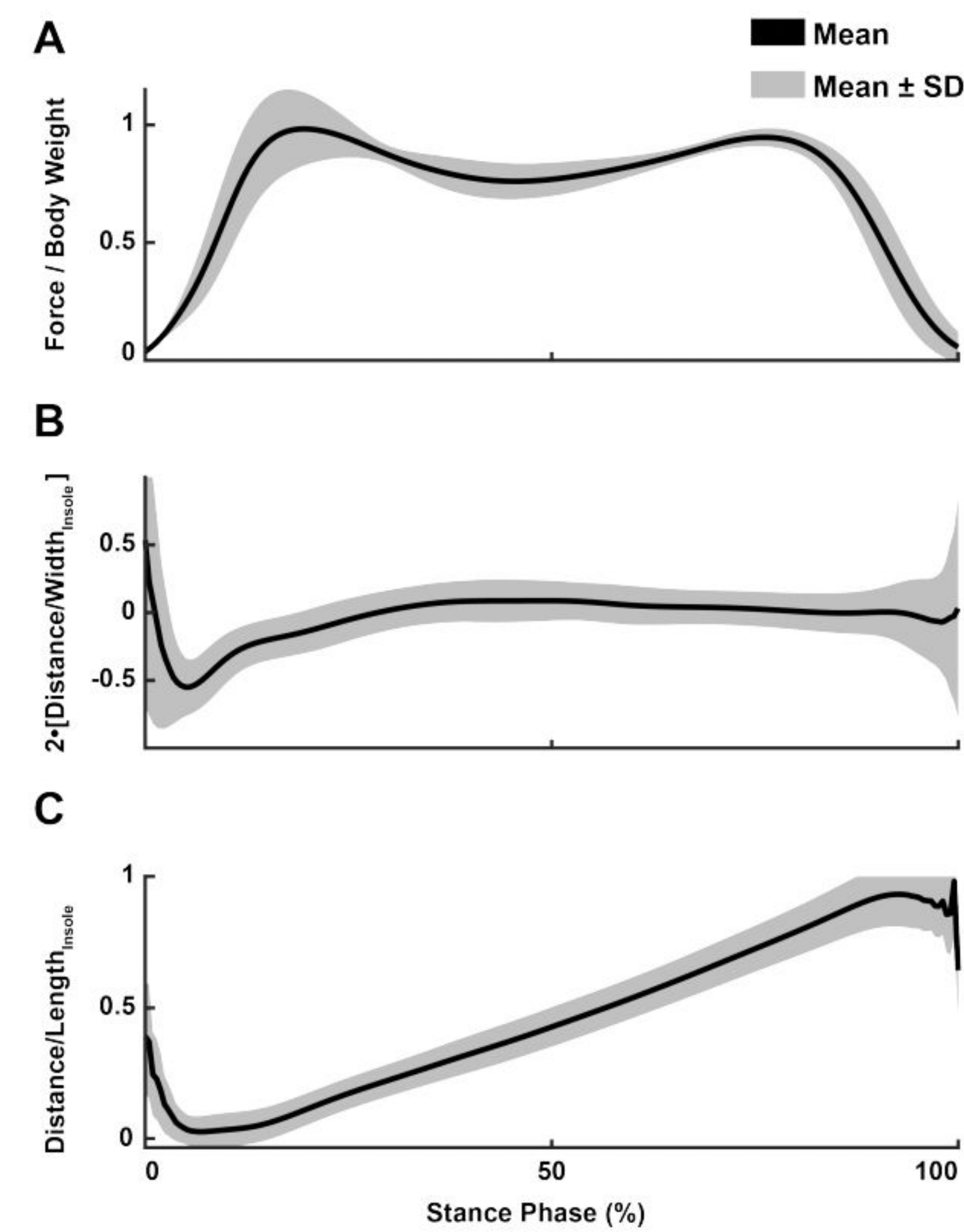
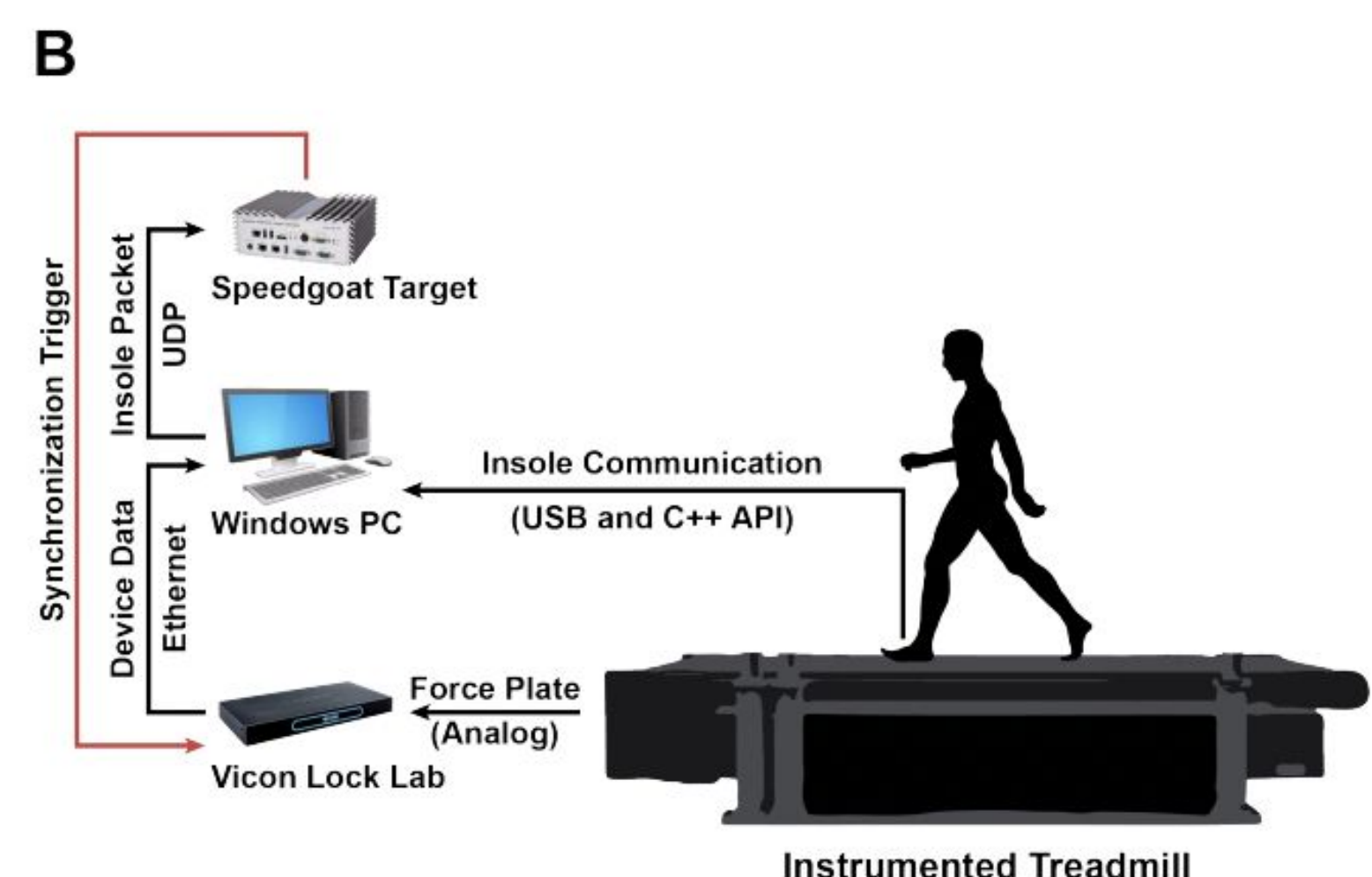
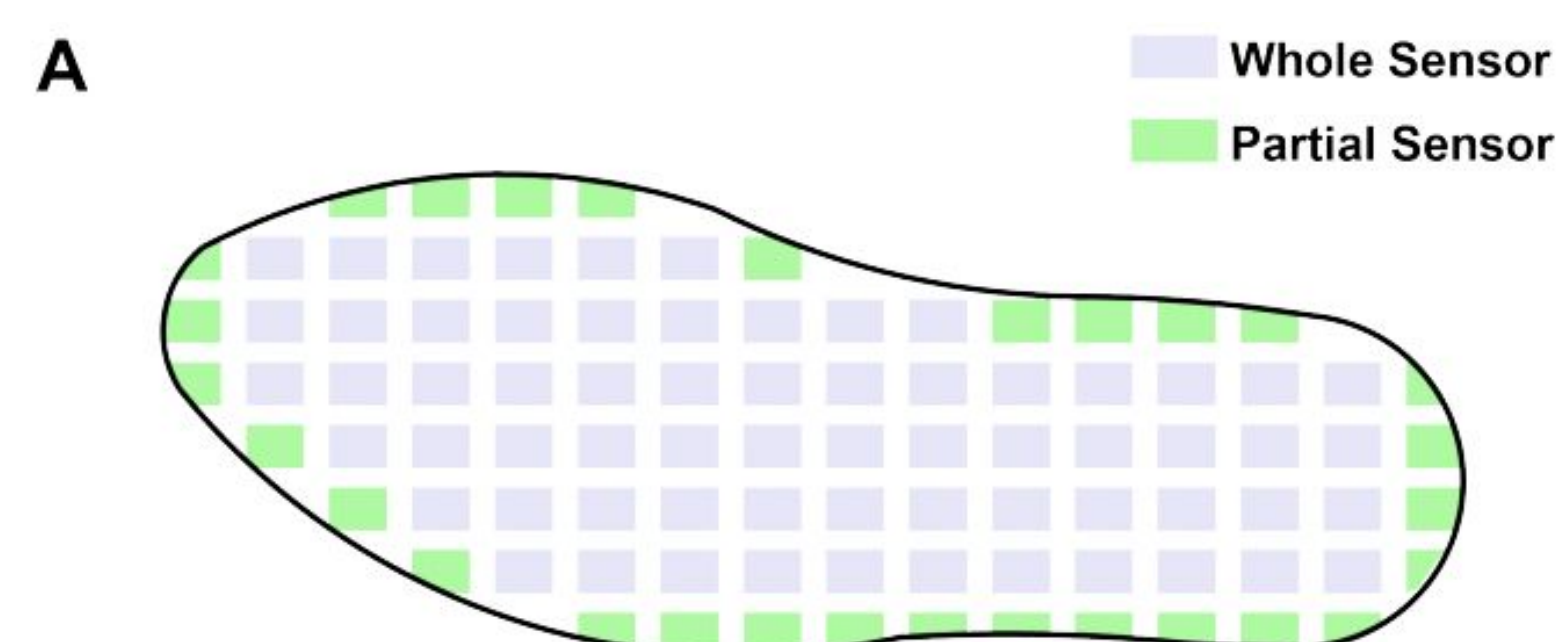


Figure 1 : Ground truth vertical GRF and center of pressure (CoP) trajectories across the stance phase (mean ± SD). Signals exhibit expected biomechanical patterns, including a double-peaked GRF profile and smooth heel-to-toe CoP progression.

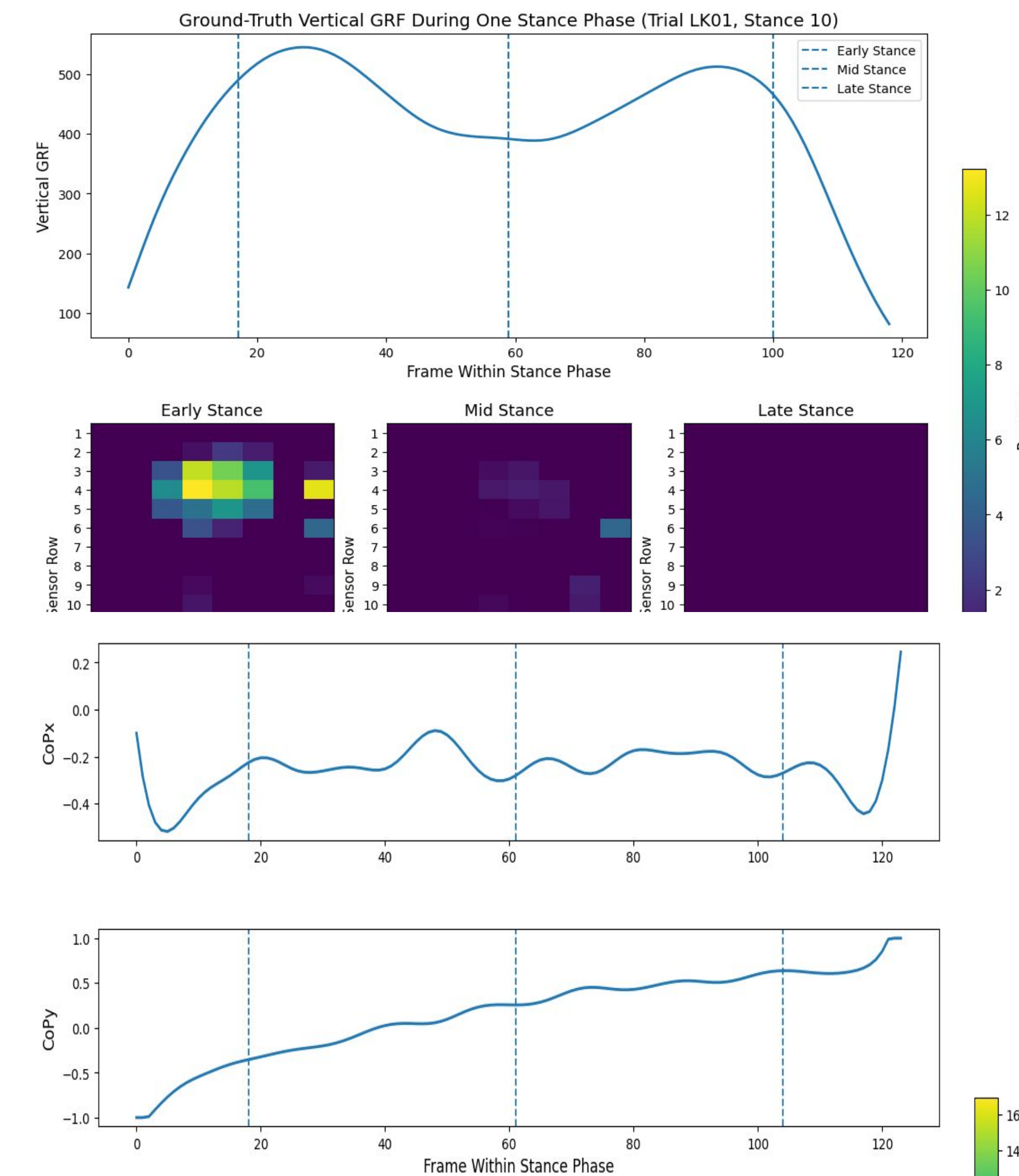


Figure 2 : GRF and CoP signals derived from raw insole data prior to model training. While general trends are preserved, increased variability and noise are present compared to ground truth measurements.

Results

1. Biomechanical Signal Consistency

- Signals retained expected gait characteristics:
 - Double-peaked vertical GRF profile
 - Smooth heel to toe CoP progression
- Trends consistent across subjects and trials
- Confirms preprocessing preserved physiologically meaningful structure

2. Cross-Dataset Model Generalization (ViT-Trans3)

- Model trained on controlled dataset (DB1) and tested on variable dataset (DB2)
- Majority of subjects showed strong Pearson correlation with ground truth
- Demonstrates robustness to:
 - Speed perturbations
 - Incline changes
 - Single foot measurements

4. Subject-Specific Variability

- One subject exhibited noticeably lower correlation
- Embedding analysis showed increased distance from global feature distribution
- t-SNE visualization confirmed separation from other subjects, suggests sensitivity to subject specific differences in data distribution

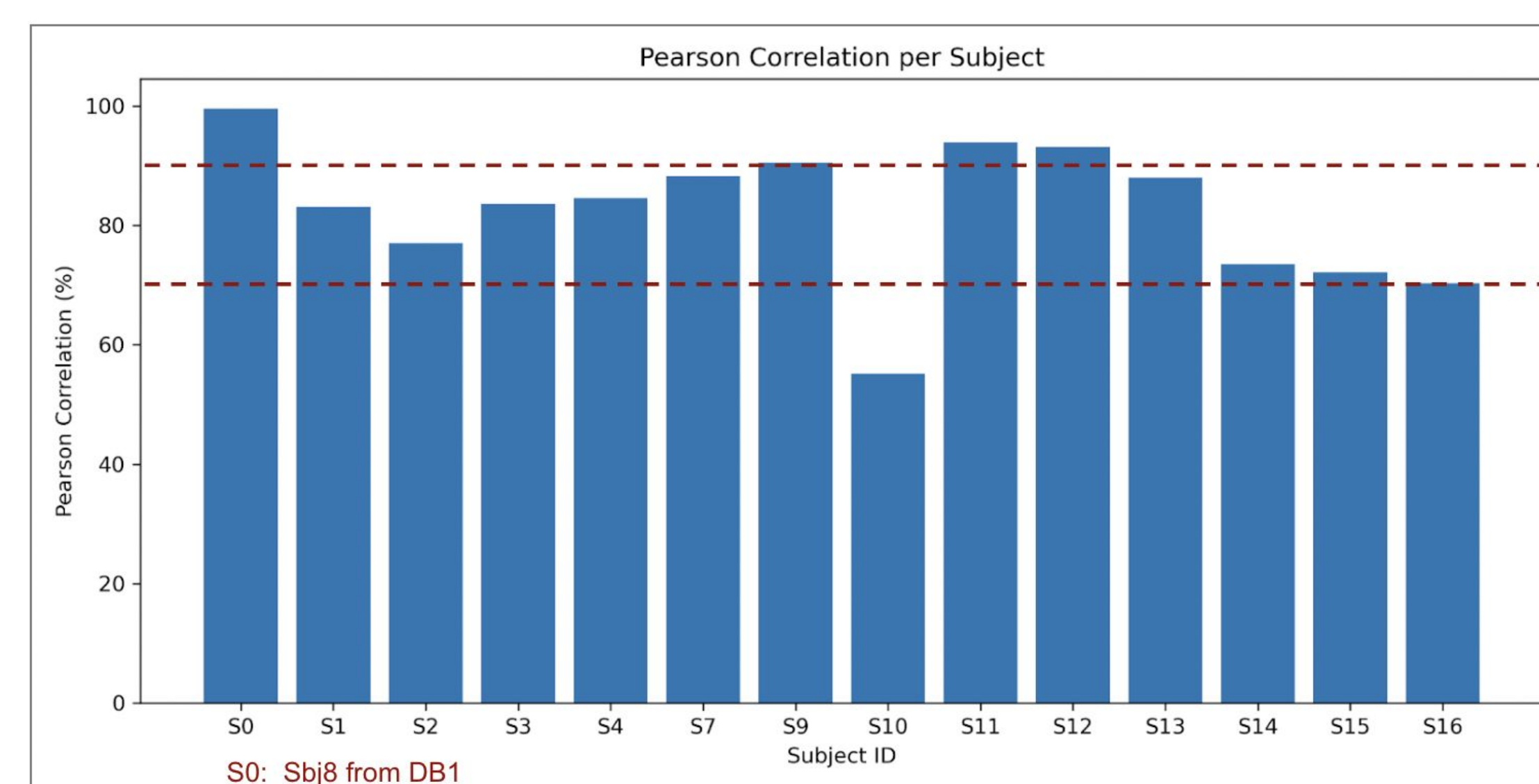


Figure 4 : Pearson correlation coefficients between predicted and ground truth signals for each subject. Most subjects show strong agreement, indicating successful model generalization, with one subject exhibiting reduced correlation.

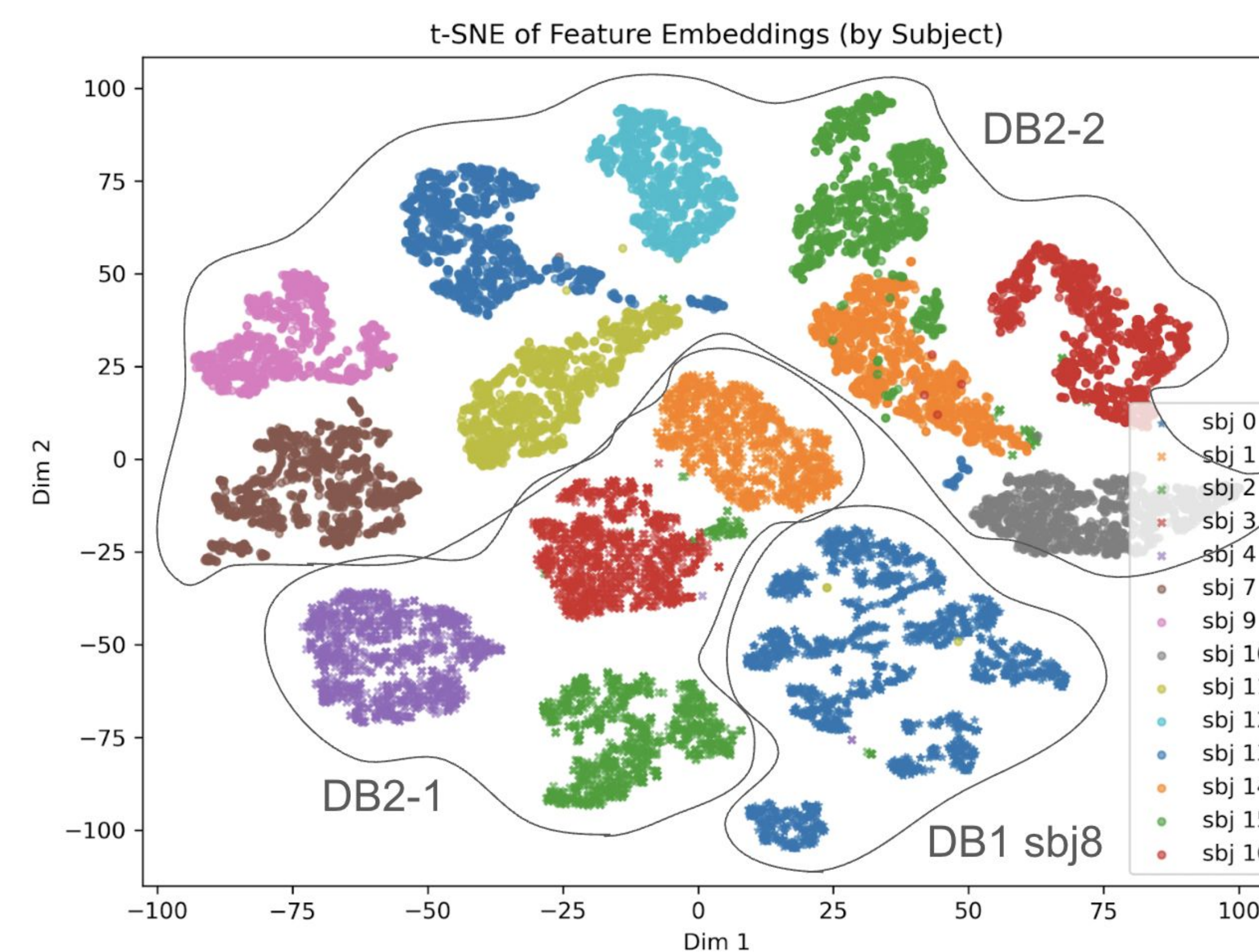


Figure 3 : t-SNE visualization of feature embeddings from the final model layer, colored by subject. Most subjects cluster closely, indicating consistent feature representations, while one subject shows clear separation, suggesting subject-specific variability in the data distribution.

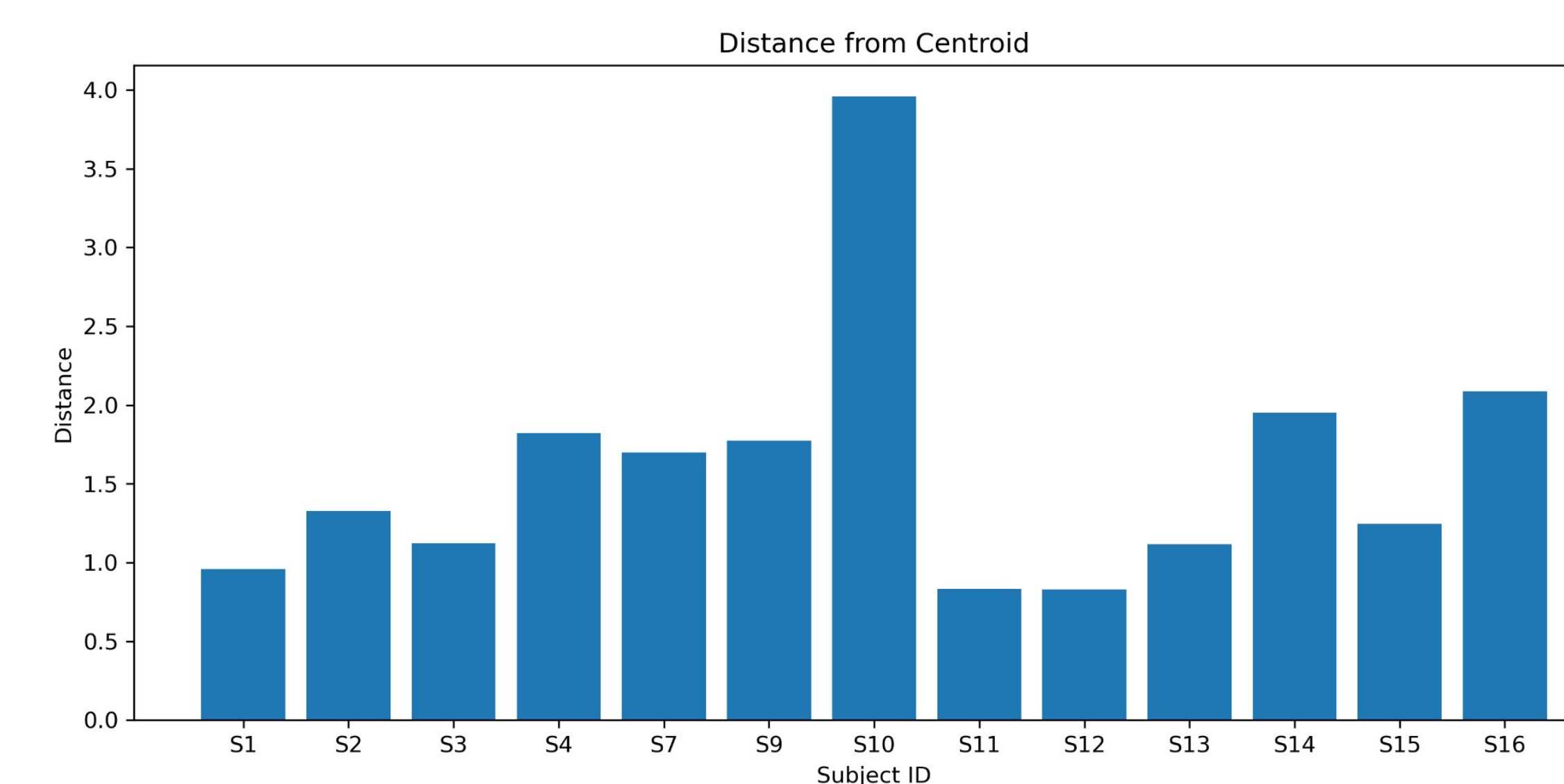


Figure 5 : Distance of each subject's feature embeddings from the global centroid. One subject shows increased deviation, indicating a distribution shift consistent with reduced model performance.

Conclusion & Discussion

- Wearable insoles enable real world GRF estimation beyond lab settings.
- Deep learning models showed strong generalization from controlled to variable walking conditions, but performance was affected by sensor inconsistencies and subject variability.
- Wearable insole systems combined with deep learning show strong potential for real world gait analysis, but robustness depends critically on data quality.

Future Directions

Expand to larger, multi subject datasets to enhance robustness across diverse gait patterns

Analyze differences between full gait cycle inputs and stance phase focused modeling to optimize prediction accuracy

Translate the pipeline to real time wearable systems for in field gait monitoring

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References

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