## Using Matrix Profile Discords for Event Detection in Treadmill Walking

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## **Summary**

Biomechanical analysis uses events to give structure to motion capture data and identify meaningful changes in the body's physical processes. Although methods have been proposed for automatic event detection, these are generally limited to gait events for participants who display regular kinematic behaviours. Here we propose an event detection method based on the Matrix Profile where discords are used to identify heel strike events during gait. Our results show that this method reliably predicts heel strike events during treadmill walking, with prediction errors that are comparable to those of existing methods. We conclude that this method merits further investigation for its ability to detect meaningful events across other activities.

### Introduction

Manually defining events across an activity is tedious and impractical for large data sets, motivating methods that automatically detect events, including using: the foot position relative to the pelvis [1]; the foot velocity relative to the pelvis [1]; and hip kinematics [2]. These methods rely on regular gait kinematic behaviour and do not extend to other activities. We propose using a Matrix Profile (MP) to predict events by identifying motifs and discords across biomechanical waveforms [3].

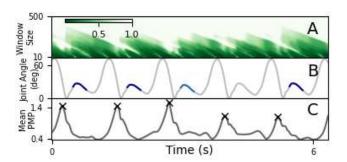
# Methods

We extracted knee flexion/extension (flex./ext.) angles during treadmill walking for 10 healthy human participants from a publicly available motion capture dataset [4]. We computed a Pan Matrix Profile (PMP) [3] for a large range of window sizes and identified motifs in two steps (Figure 1a). First, we extracted candidate motifs from the PMP whose nearest neighbour was within 1 standard deviation. Second, motifs were those candidates in the top 1% of cumulative coverage as calculated from the set of its matching neighbour traces (Figure 1b). We calculated the mean MP across motifs' window sizes marking local maxima as discords (Figure 1c).

Denoting the ith discords' time stamp as  $D_i$  we modelled heel strike events (HS) using (1). Through cross-validation, we solved for m for each set of 9 participants by minimizing the mean square error, resulting in values of  $0.106\pm0.002$ . We used the value of m calculated for each set of participants to predict HS for the held out participant using (1).

$$HS = D_i + (D_i - D_{i-1}) * m$$
 (1)

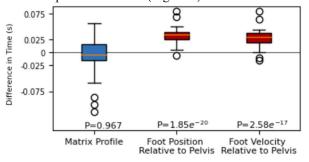
These predicted HS, along with HS detected using literature methods [1,2] were evaluated by their difference to gold standard HS detected using concurrent force platform data.



**Figure 1: A:** PMP of an individual's knee flex./ext. **B:** Knee flex./ext. with a candidate motif (light blue) and its matching neighbor traces (dark blue). **C:** Mean MP from **A** across windows sizes containing motifs with local maxima indicating discords.

## **Results and Discussion**

Our MP-based method reliably predicted HS during gait with no false negatives or false positives. The method using hip kinematics [2] predicted many false positives; we therefore excluded it from the rest of our analysis. Although our MP-based method was more variable than the others, the mean difference between its predictions and the gold standard was not significantly different from 0 while the other two methods' predictions were (Figure 2).



**Figure 2**: Differences between predicted and gold standard HS. Two-tailed t-test p-values are shown for whether the difference is 0. We use the Bonferroni Correction to adjust a significance level of 0.05 to 0.0167.

## Conclusions

Our MP-based method successfully predicted HS during gait. Since it does not explicitly model underlying kinematic behaviours, we believe that it merits further investigation for event detection in other activities as well.

### References

- [1] Zeni JA et al. (2008). Gait Posture, 27: 710-714.
- [2] De Asha AR et al. (2012). Gait Posture, **36:** 650-652.
- [3] Keough et al. (2019). *IEEE ICBK*, **2019**: 175-182.
- [4] Scherpereel et al. (2023). Sci Data, 10: 9.