

A multivariate multilevel longitudinal functional model for repeatedly observed human movement data

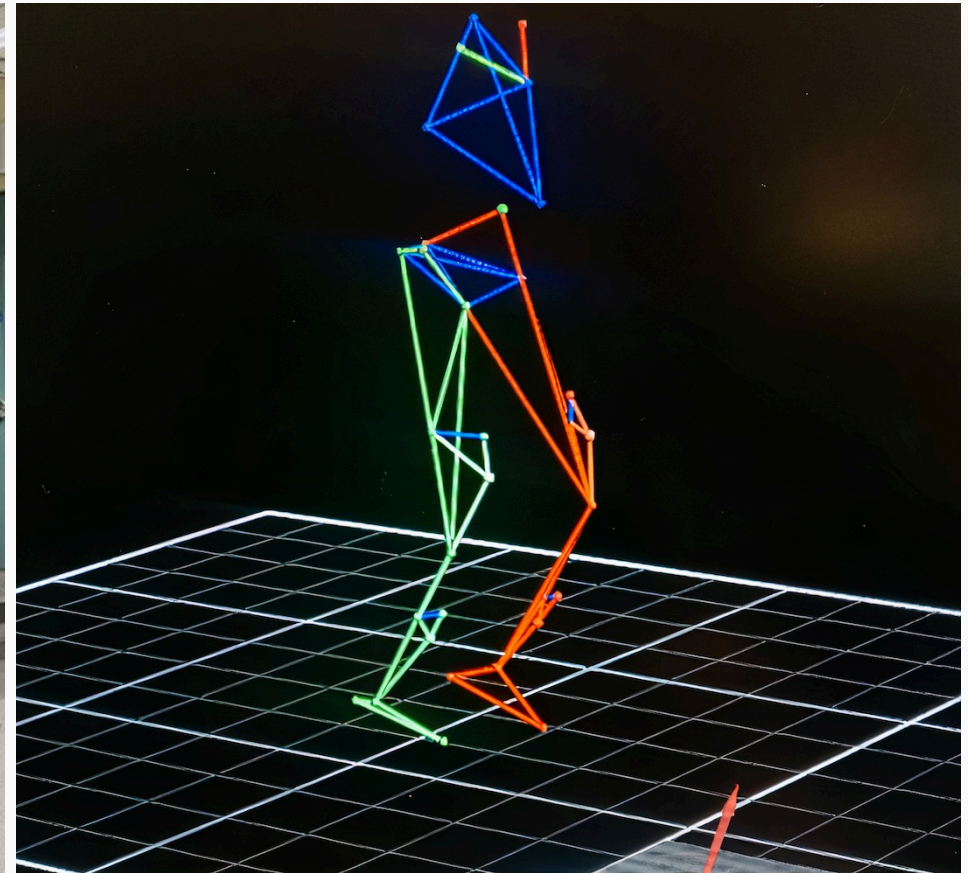
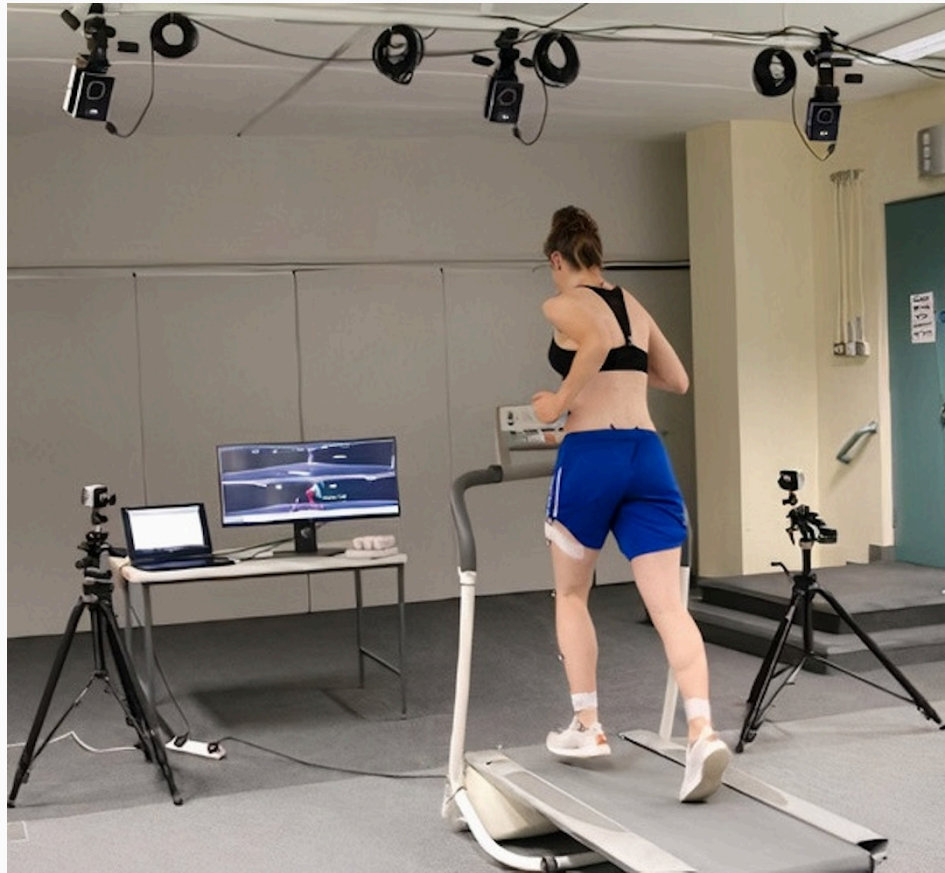
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Kieran Moran · Siobhan O'Connor · Enda Whyte · Norma Bargary

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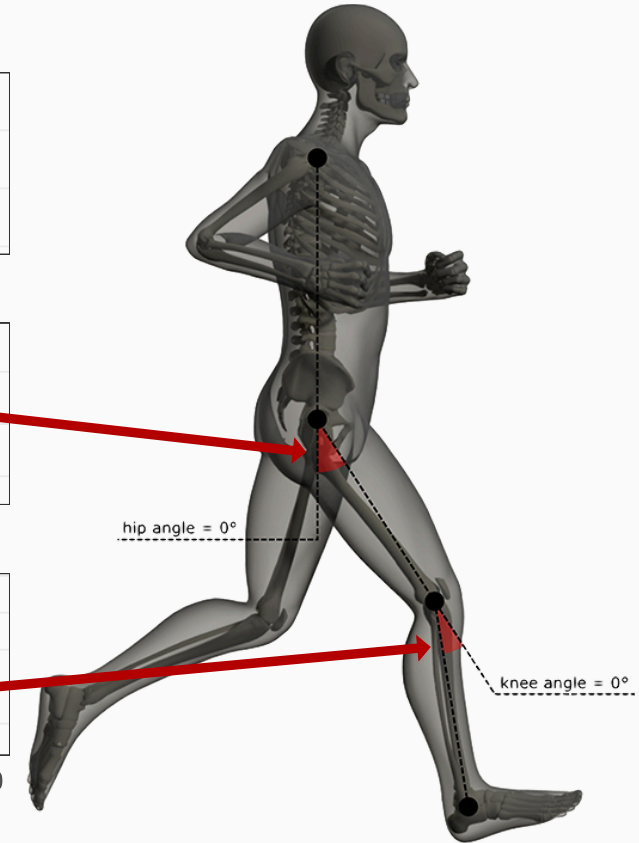
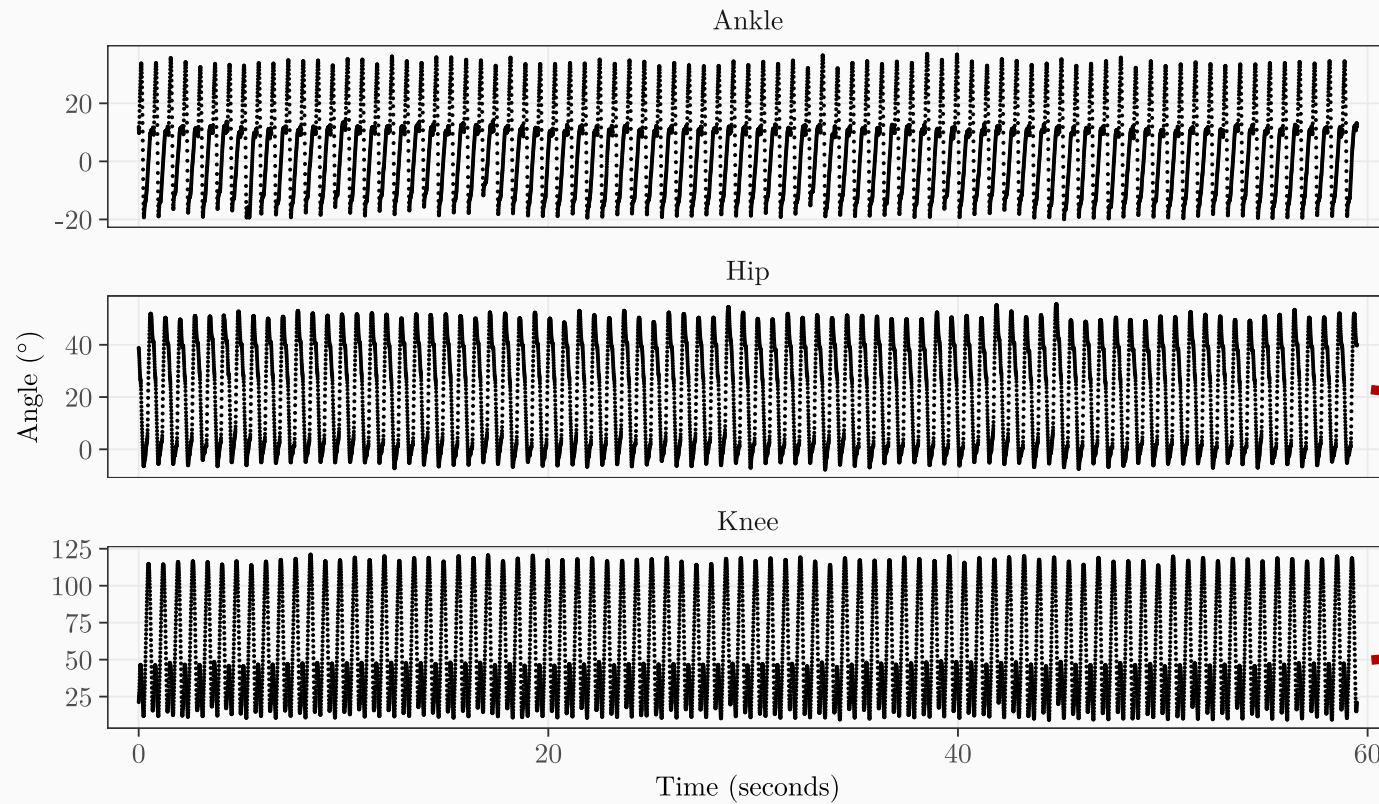


RISC dataset

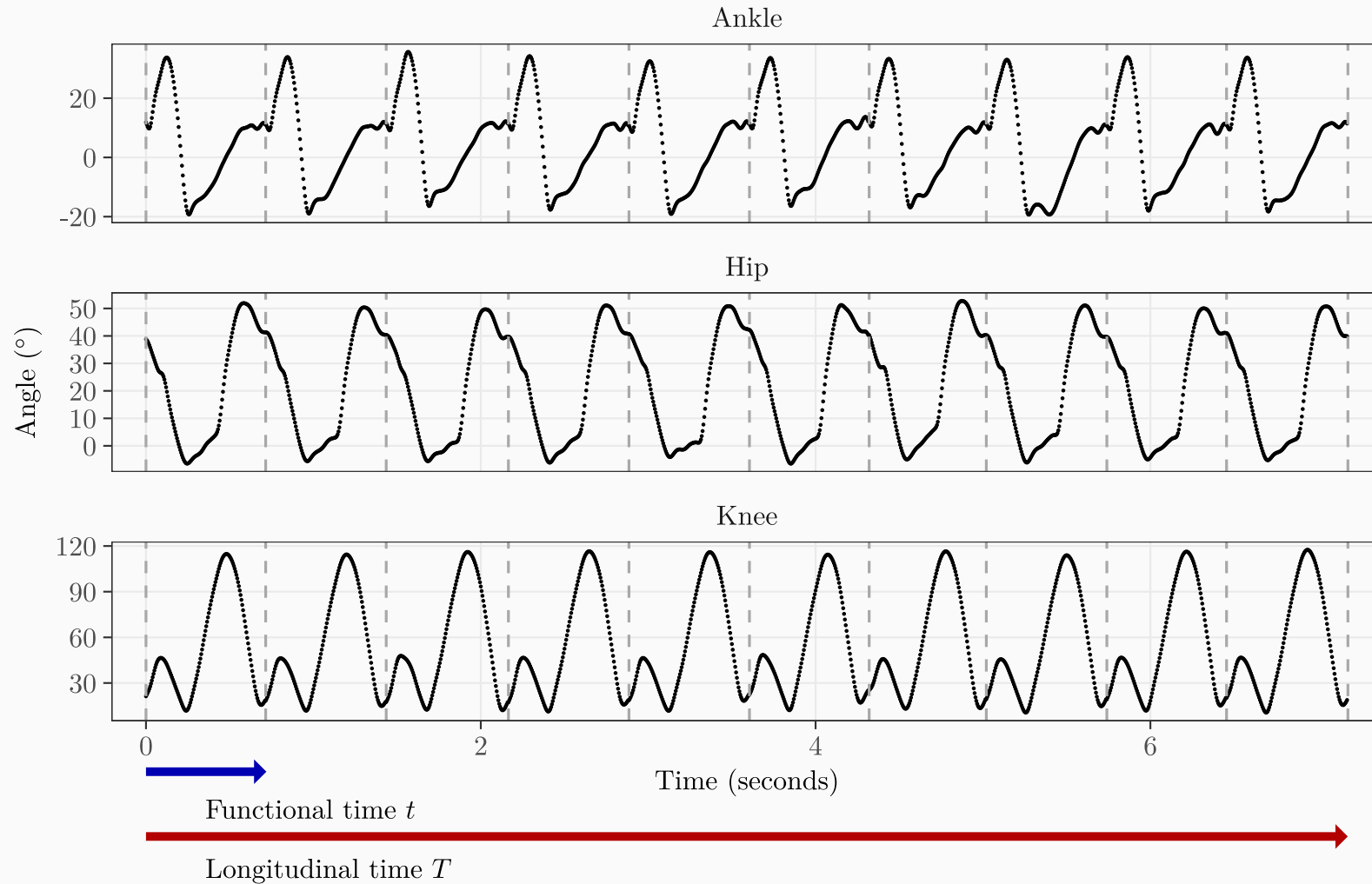


@DCU_RISC_Study

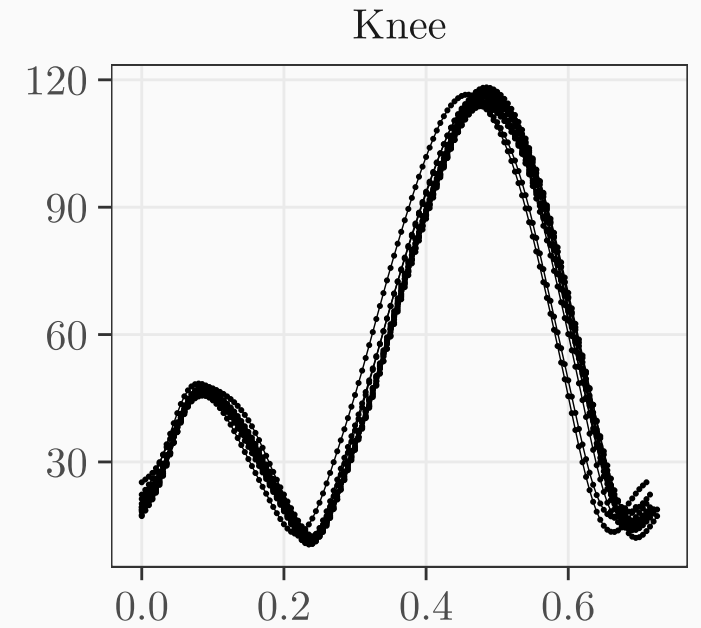
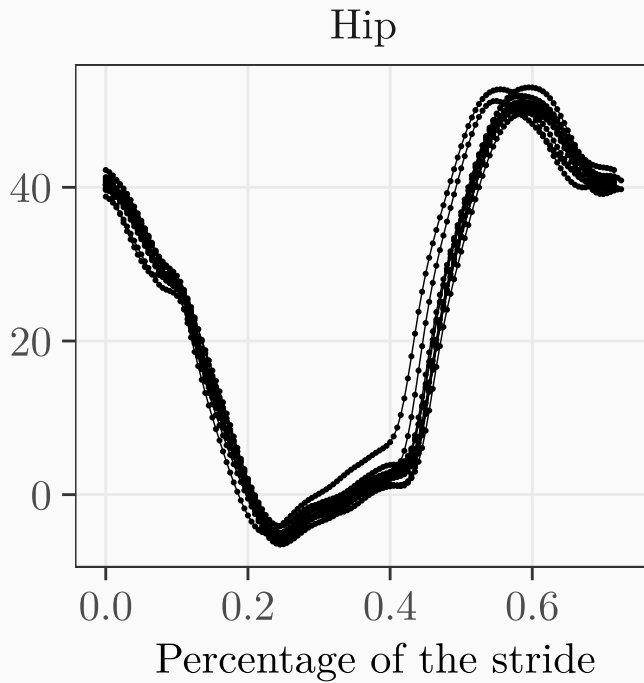
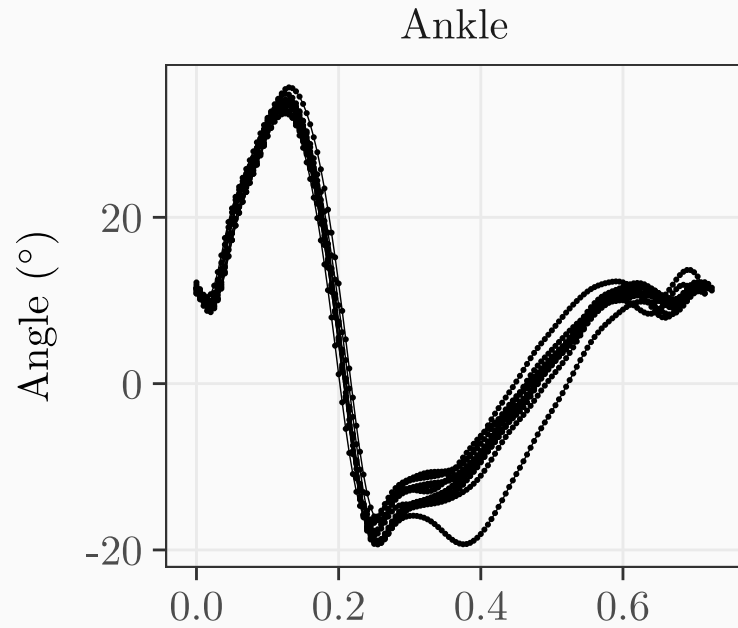
(Almost) Raw data



Segmented data

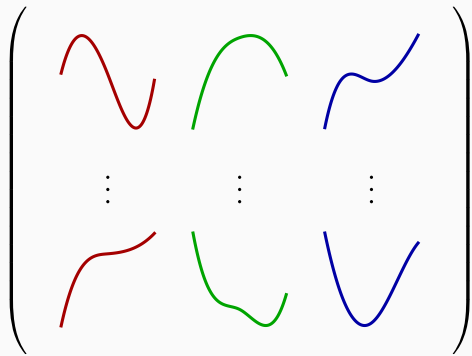


Segmented data

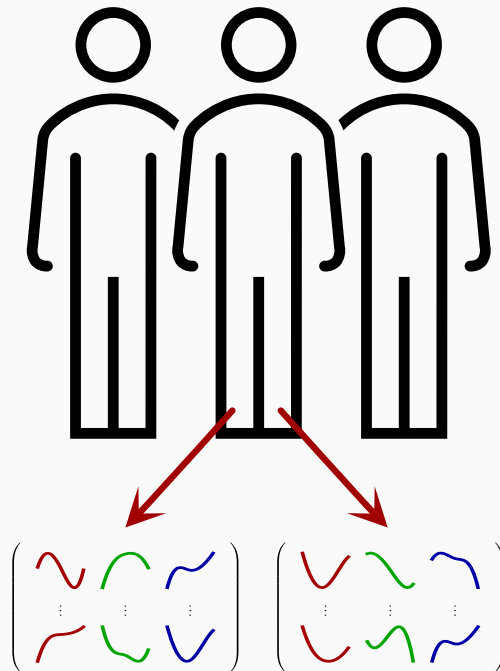


Data characteristics

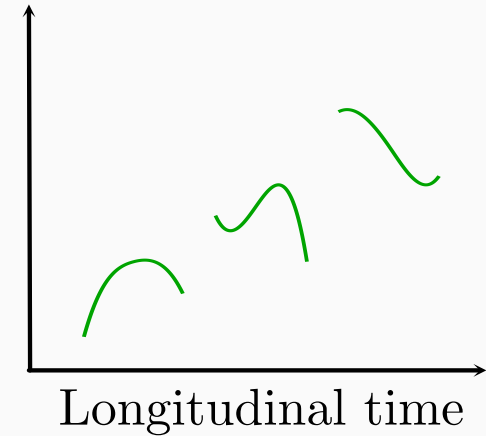
Multivariate



Multilevel



Longitudinal



Multivariate multilevel longitudinal functional model

$$\mathbf{y}_{ijl}(t) = \mu(\mathbf{x}_{ijl}, t) + \mathbf{u}_i(t, T_{ijl}) + v_{ij}(t, T_{ijl}) + \varepsilon_{ijl}(t)$$

$$\mathbf{y}_{ijl}(t) = \left(y_{ijl}^{(hip)}(t), y_{ijl}^{(knee)}(t), y_{ijl}^{(ankle)}(t) \right)^\top$$

$$i = 1, \dots, N$$

$$j = \{\text{left}, \text{right}\}$$

$$l = 1, \dots, n_{ij}$$

$$t \in [0, 100\%]$$

Multivariate multilevel longitudinal functional model

$$\mathbf{y}_{ijl}(t) = \mu(\mathbf{x}_{ijl}, t) + \mathbf{u}_i(t, T_{ijl}) + v_{ij}(t, T_{ijl}) + \varepsilon_{ijl}(t)$$

“Fixed effects”

Mean function and effect of scalar covariates,
e.g. speed, sex, injuries, ...

Multivariate multilevel longitudinal functional model

$$\mathbf{y}_{ijl}(t) = \mu(\mathbf{x}_{ijl}, t) + \mathbf{u}_i(t, T_{ijl}) + v_{ij}(t, T_{ijl}) + \varepsilon_{ijl}(t)$$

The diagram illustrates the decomposition of the model into subject mean and subject and side mean components. The term $\mathbf{u}_i(t, T_{ijl})$ is highlighted with a blue box and labeled "Subject mean". The term $v_{ij}(t, T_{ijl})$ is highlighted with a pink box and labeled "Subject and side mean". The variable $T \in [0, 1]$ is shown above the equation, with arrows pointing to the T_{ijl} terms in both \mathbf{u}_i and v_{ij} .

Multivariate multilevel longitudinal functional model

$$\mathbf{y}_{ijl}(t) = \mu(\mathbf{x}_{ijl}, t) + \mathbf{u}_i(t, T_{ijl}) + v_{ij}(t, T_{ijl}) + \varepsilon_{ijl}(t)$$

Smooth random error



Multivariate multilevel longitudinal functional model

$$\mathbf{y}_{ijl}(t) = \mu(\mathbf{x}_{ijl}, t) + \mathbf{u}_i(t, T_{ijl}) + v_{ij}(t, T_{ijl}) + \varepsilon_{ijl}(t)$$

Assume an estimate
has been subtracted

Focus on modeling this part

➔ Complex functional model, varying over two timescales t and T

Key ideas

$$\mathbf{y}_{ijl}(t) = \sum_{k=1}^K y_{ijl,k}^* \phi_k(t)$$

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Multivariate basis functions that do not depend on longitudinal T

For univariate longitudinal functional data:

Park and Staicu (2015)
Lee et al. (2019)
Li et al. (2022)

Key ideas

$$\mathbf{y}_{ijl}(t) = \sum_{k=1}^K \mathbf{y}_{ijl,k}^* \phi_k(t)$$

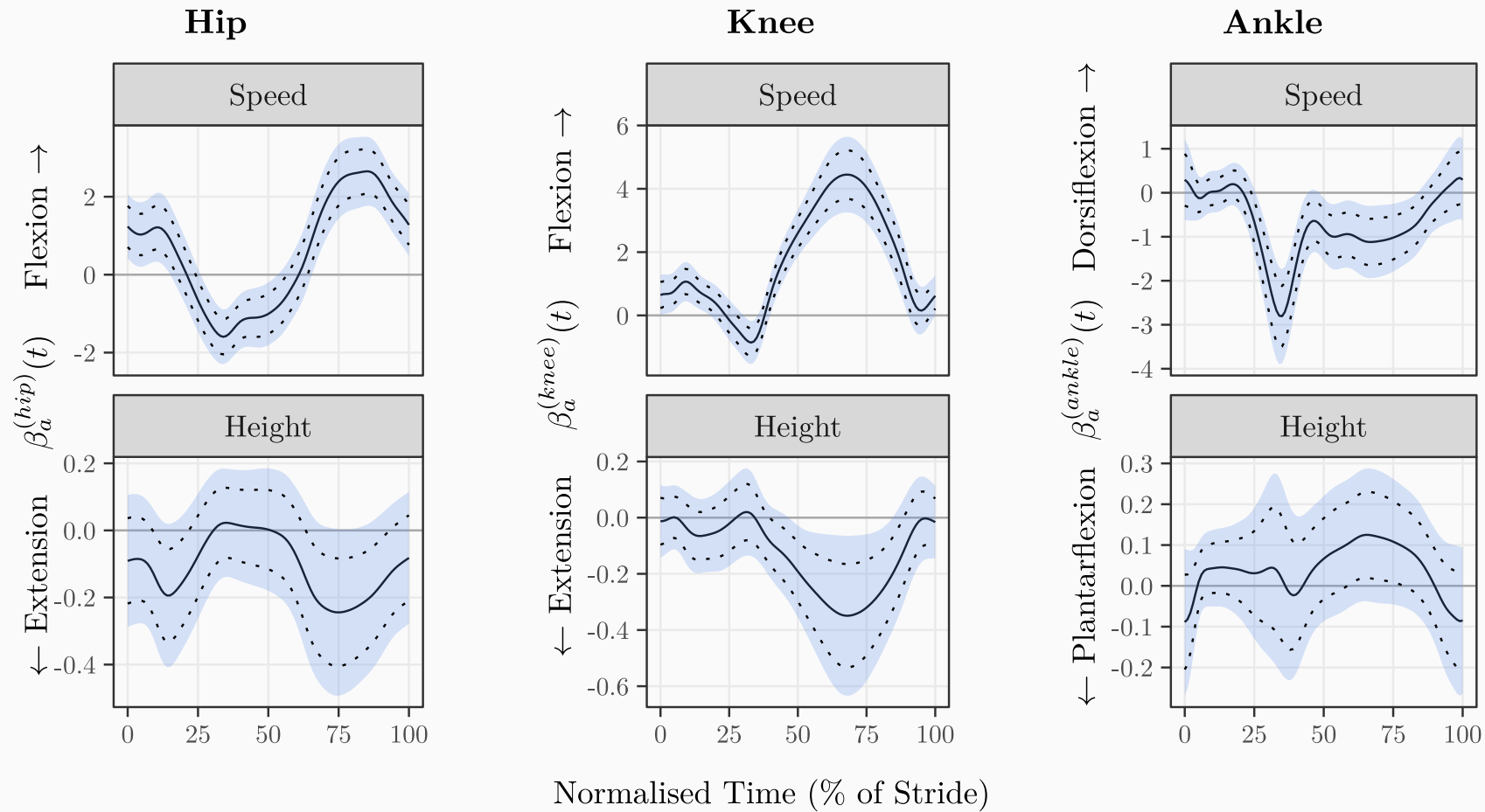
Basis coefficients capturing
the longitudinal trends

$$\mathbf{y}_{ijl,k}^* = \mathbf{u}_{i,k}^*(T_{ijl}) + \mathbf{v}_{ij,k}^*(T_{ijl}) + \epsilon_{ijl,k}^*$$

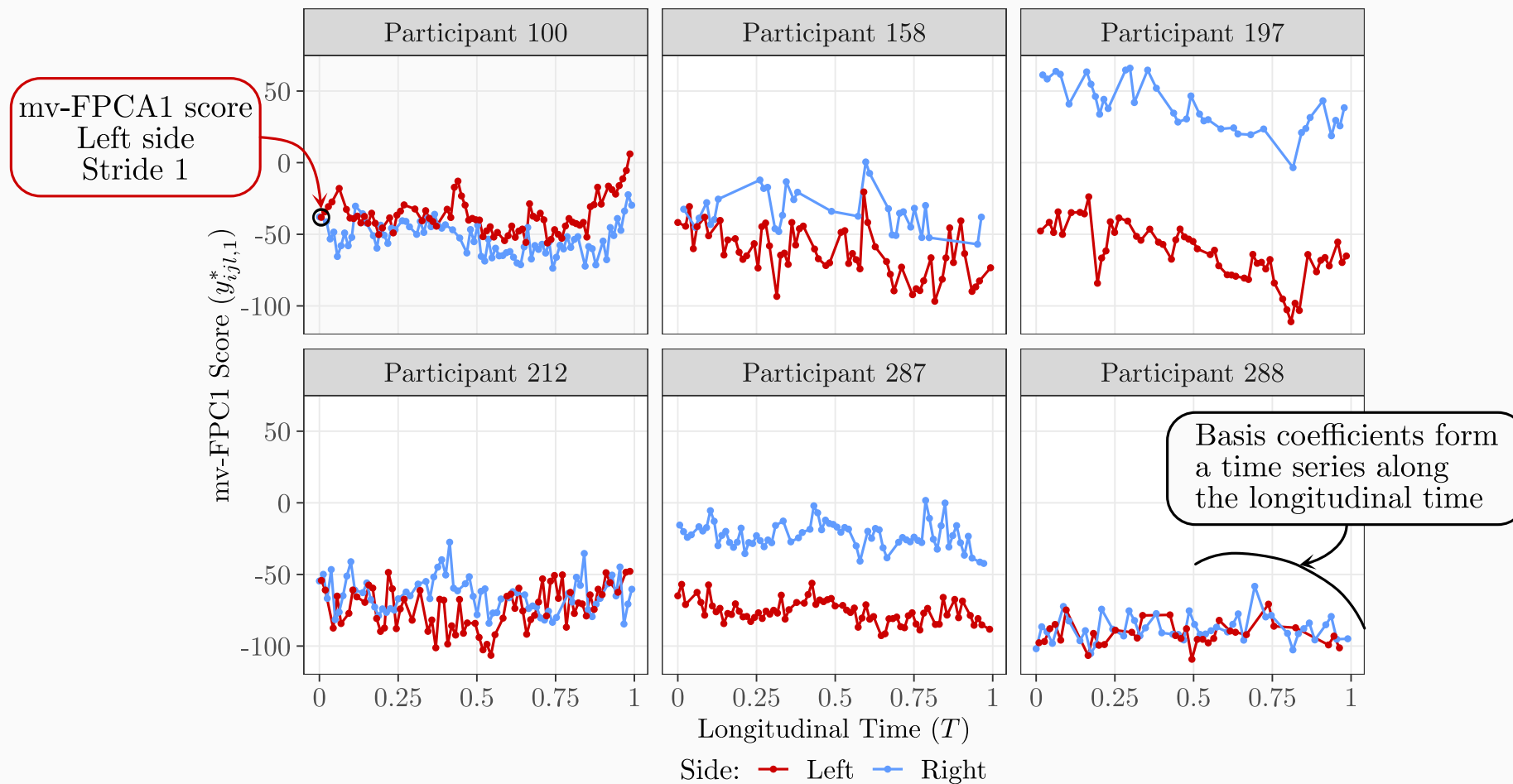
Functional Multilevel model (Di et al., 2009):

For each of the basis coefficients k
 $T =$ longitudinal time

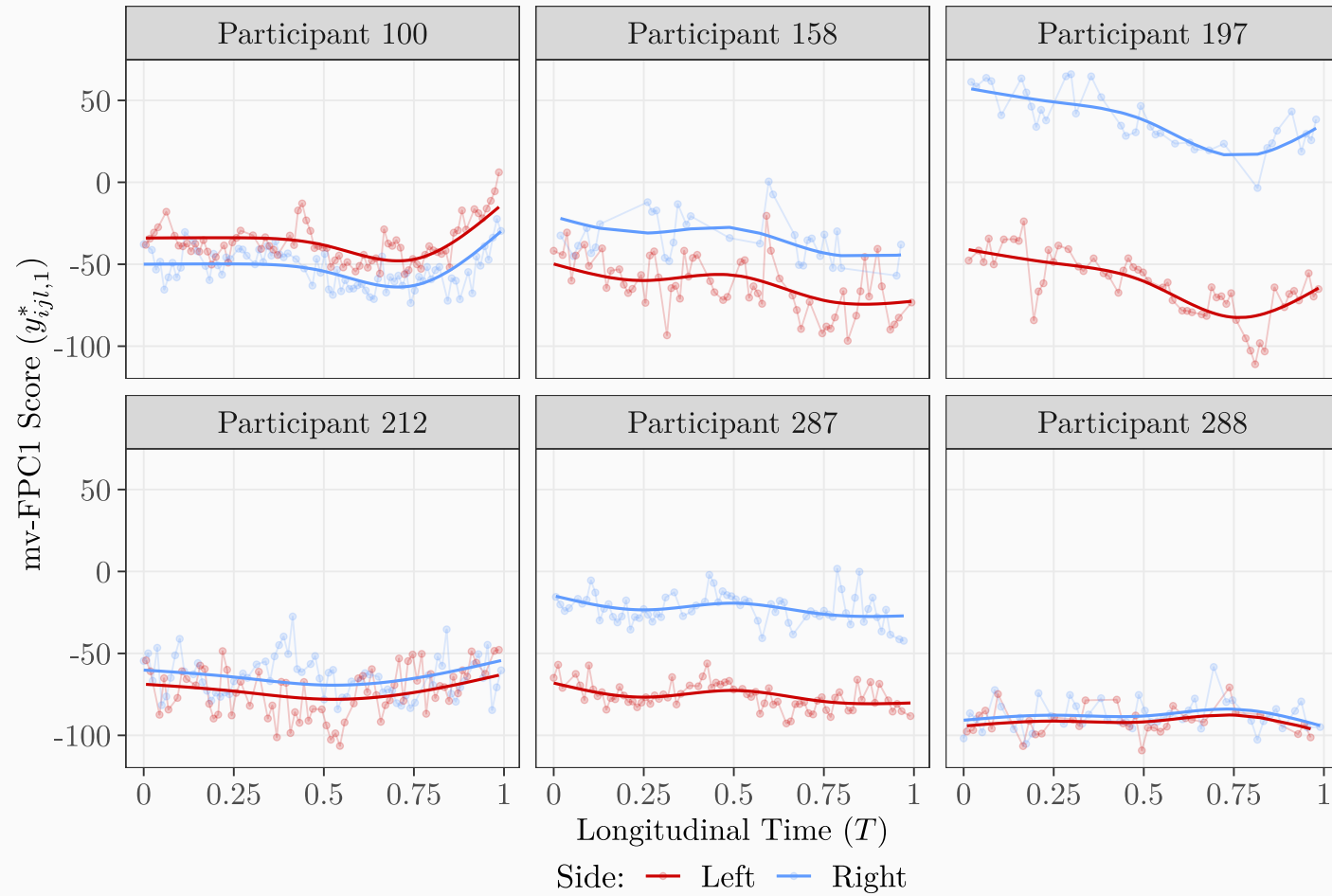
Fixed effects



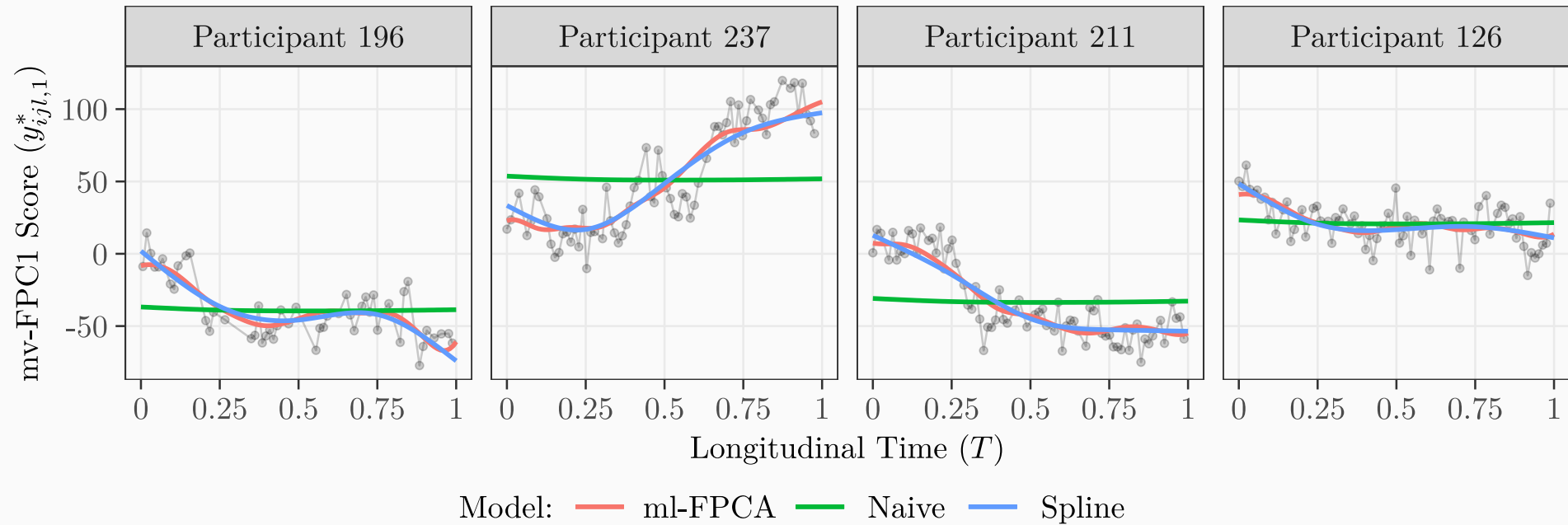
ml-FPCA of the mv-FPCA scores



ml-FPCA of the mv-FPCA scores



ml-FPCA of the mv-FPCA scores



Individual analysis for one participant



Takeaway ideas

- We decomposed the main sources of variability in the data by:
 - capturing multivariate functional dependence using a pooled mv-FPCA basis;
 - modeling the multilevel longitudinal trends through the mv-FPCA scores.
- We identified very simple longitudinal trends.
- It can be improved by relaxing and imposing assumptions.

Thank you for your attention!

References

Di, C., C. M. Crainiceanu, B. S. Caffo, et al. (2009). “Multilevel Functional Principal Component Analysis”. In: *The annals of applied statistics* 3.1, pp. 458–488. ISSN: 1932-6157. DOI: [10.1214/08-AOAS206SUPP](https://doi.org/10.1214/08-AOAS206SUPP).

Lee, W., M. F. Miranda, P. Rausch, et al. (2019). “Bayesian Semiparametric Functional Mixed Models for Serially Correlated Functional Data, With Application to Glaucoma Data”. In: *Journal of the American Statistical Association* 114.526, pp. 495–513. ISSN: 0162-1459. DOI: [10.1080/01621459.2018.1476242](https://doi.org/10.1080/01621459.2018.1476242).

Li, R., L. Xiao, E. Smirnova, et al. (2022). “Fixed-Effects Inference and Tests of Correlation for Longitudinal Functional Data”. In: *Statistics in Medicine* 41.17, pp. 3349–3364. ISSN: 1097-0258. DOI: [10.1002/sim.9421](https://doi.org/10.1002/sim.9421).

Park, S. Y. and A. Staicu (2015). “Longitudinal Functional Data Analysis”. In: *Stat* 4.1, pp. 212–226. ISSN: 2049-1573. DOI: [10.1002/sta4.89](https://doi.org/10.1002/sta4.89).