P2-P-60

Can machine learning techniques reduce the number of inertial sensors in real life gait analysis?

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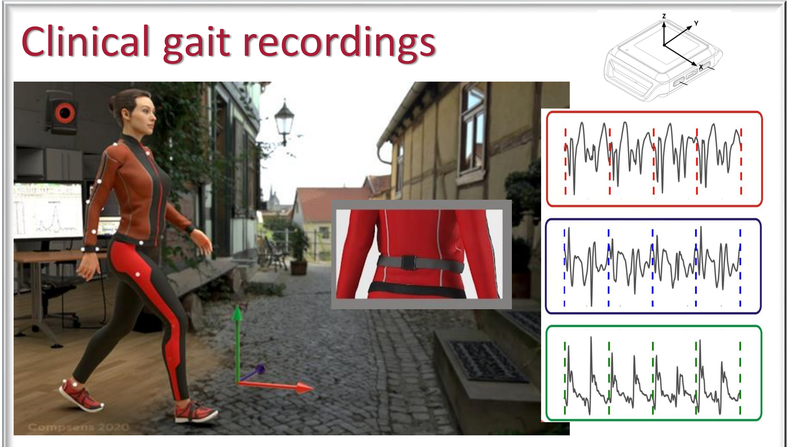
Background

- Wearable inertial measurement units (IMU) enable large-scale **multicenter studies of everyday gait analysis** in patients with rare neurodegenerative diseases such as **cerebellar ataxia**.
- Reliable and feasible **one-sensor systems** are particularly promising for upcoming therapy studies, as these **optimize patient convenience** and **reduce costs.**
- Here, we compare relative errors of 14 gait features assessed by **three sensors (3S) vs a single sensor (1S)** with no or previously generated feet signals (1S+2S) .
- Using retraining and LRP, we **determine driving elements** of the input signals to predict individuals' gait features.
- **Aim**: Prediction of ataxic-sensitive gait features with small relative errors (<5%) using **1D-CNN**-assisted one-sensor systems in everyday life.

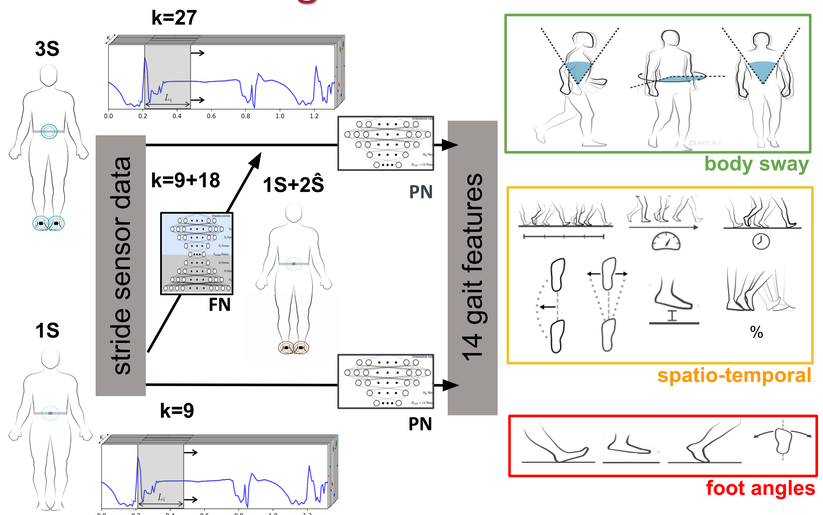
Clinical gait recordings



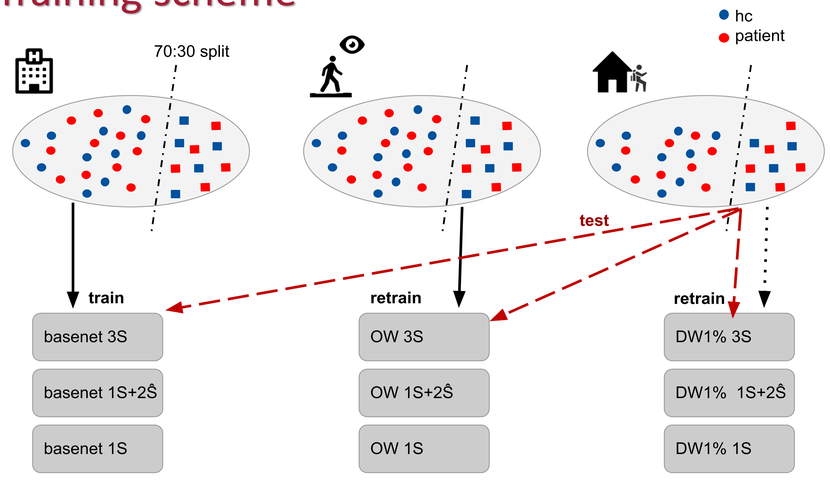
47 healthy controls and 59 patients with cerebellar ataxia were recorded by three wearable IMU-sensors (APDM Opals) on both feet and the hip.

Condition	Description	#strides
Lab-Based Walking (LBW)	Subjects walk along 50m indoor corridor at preferred speed including one turn.	10715
Supervised free walking (SFW)	Subjects walk freely in the clinics for 5-10 minutes, including turnings, walking stairs & up-/downhill	61877
Real Life Walking (RLW)	Subjects record free-living movements inside and outside their homes for 3-5 hours	427519

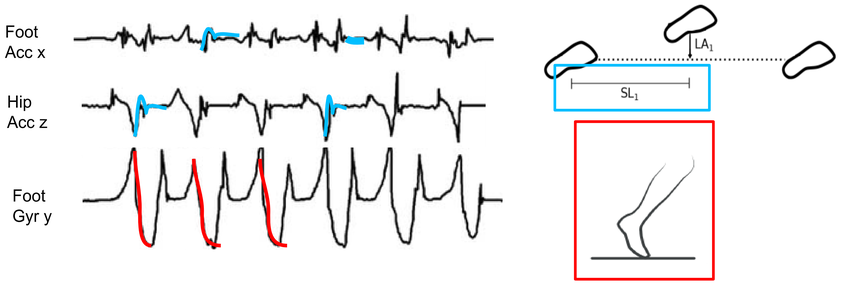
Machine learning architecture



Training scheme



Explainability motivation



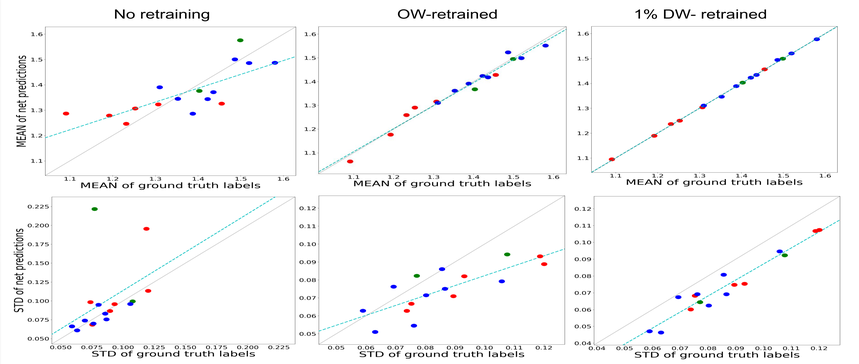
Which raw data sections are relevant for which gait parameter?

Relative errors for daily strides

Rel. error after retraining	real feet (3S) OW	real feet (3S) DW1%	pred. feet(1S+2) OW	pred. feet(1S+2) DW1%	hip(1S) OW	hip(1S) DW1%
stride duration [s]	0.72%	0.49%	1.39%	0.95%	1.19%	0.93%
gait speed [m/s]	2.53%	1.41%	3.82%	2.25%	4.13%	2.36%
stride length [m]	2.56%	1.49%	4.05%	2.18%	4.37%	2.35%
double support	3.26%	2.18%	7.70%	4.14%	7.74%	4.15 %
circumduction [m]	17.31%	14.24%	35.81%	28.70%	38.23%	28.77%
foot elevation [m]	32.00%	22.83%	39.57%	30.20%	41.88%	31.91%
lateral dev. [m]	49.82%	37.19%	74.85%	64.39%	72.47%	62.49%
pitch at TO [°]	2.47%	1.52%	6.25%	3.16%	6.61%	3.16 %
pitch at HS [°]	5.17%	3.50%	10.64%	7.00%	10.22%	6.90%
pitch at MS [°]	10.57%	8.17%	21.87%	15.53%	22.98%	15.18%
toe out[°]	34.77%	23.16%	84.41%	52.43%	85.43%	52.03%
transverse ROM [°]	8.96%	6.82 %	11.35%	7.61%	10.20%	7.11%
coronal ROM [°]	11.11%	6.73 %	9.88%	5.70%	8.81%	5.80%
sagittal ROM [°]	26.31%	19.21%	26.46%	18.06%	26.05%	18.86%

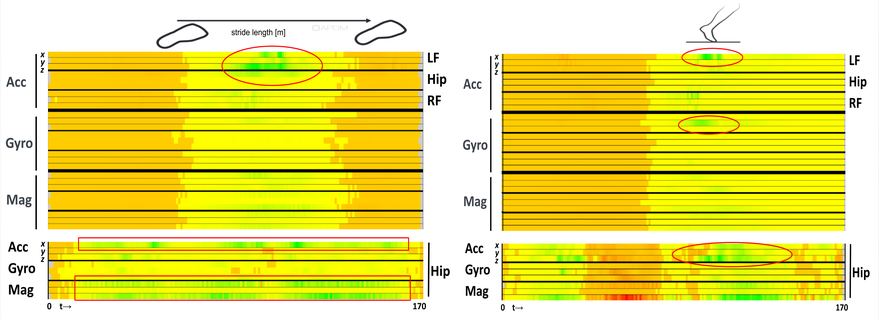
→ 1D-CNNs predict important gait features with low rel. error!

Effects of individual retraining



→ Individual retraining on pre-recorded gait data is beneficial!

Layerwise-Relevance-Propagation



→ 1D-CNNs learn meaningful representations for daily strides!

Acknowledgements

The authors thank the International Max Planck Research School for Intelligent Systems (IMPRS-IS) for supporting Jens Seemann. This work was supported by Else Kröner-Fresenius-Stiftung: Project ClinbrAIn.