WalkEar

Holistic gait monitoring using earables

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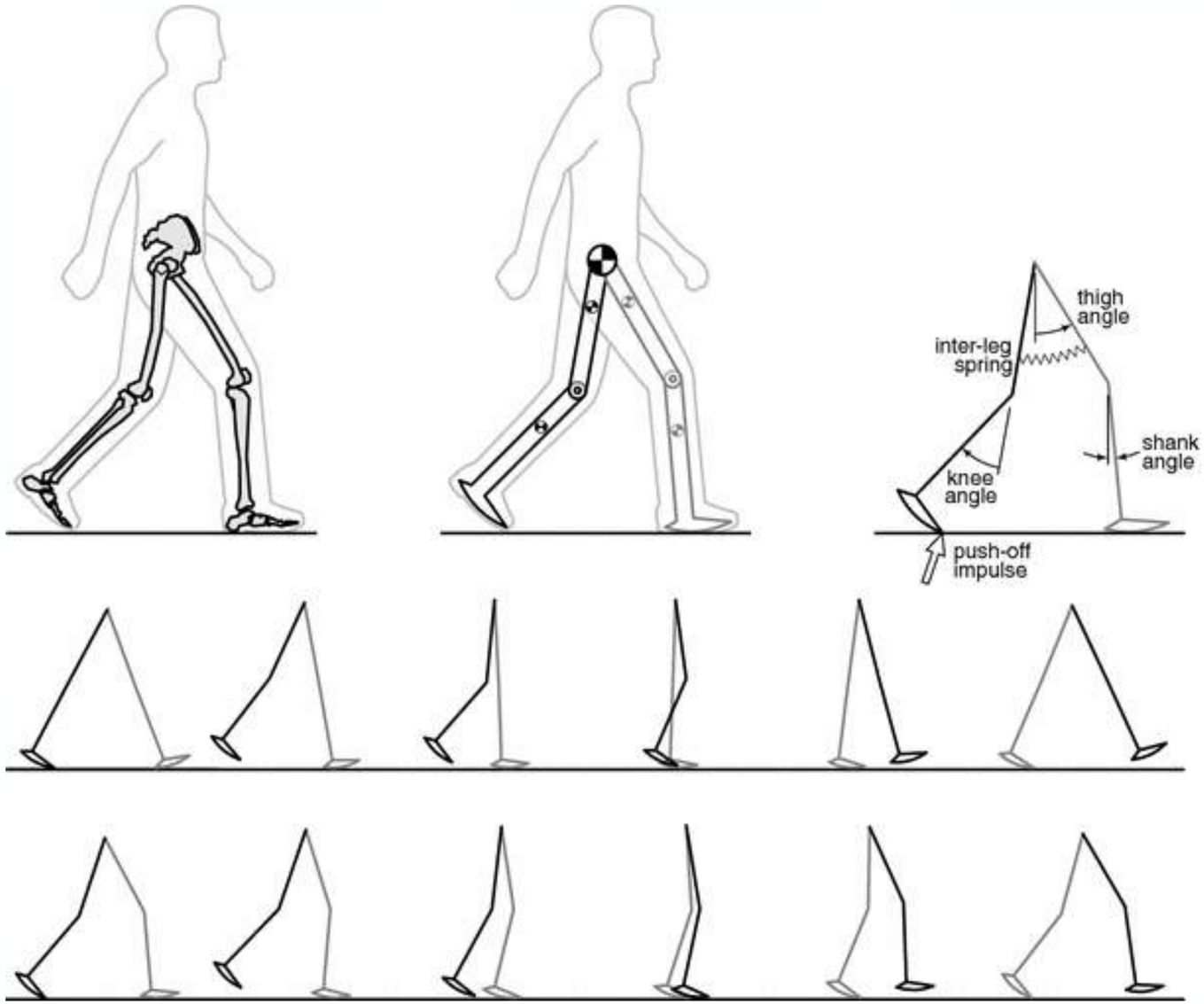
Gait

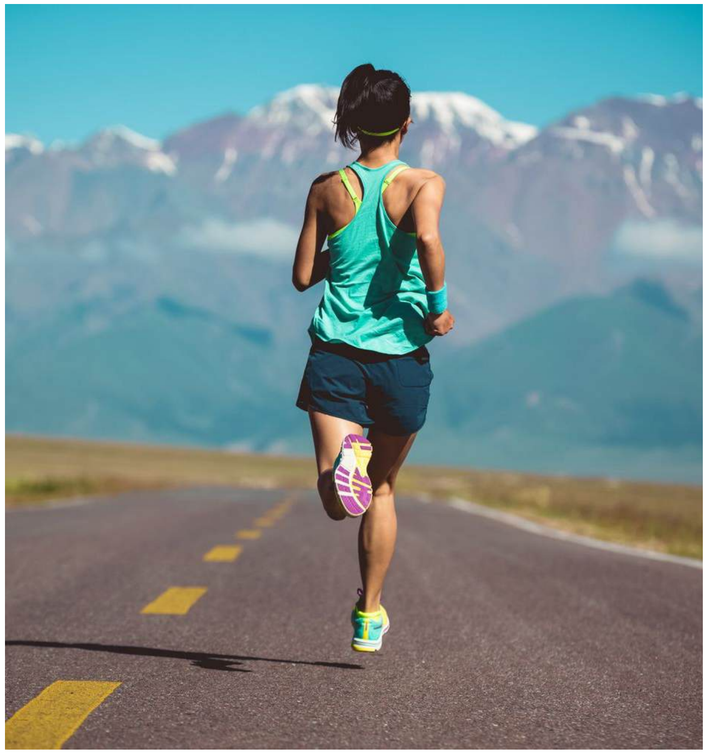
“The sixth vital sign”

- Individual
- Complex
- Depends on a multitude of factors



Monitoring gait behaviour

Sports and fitness applications



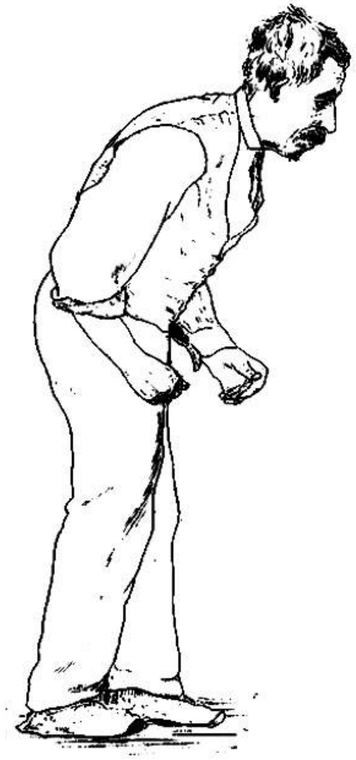
Measuring
Performance

Tracking Injury
Risk

Monitoring gait behaviour

Healthcare applications

Monitoring gait disorders



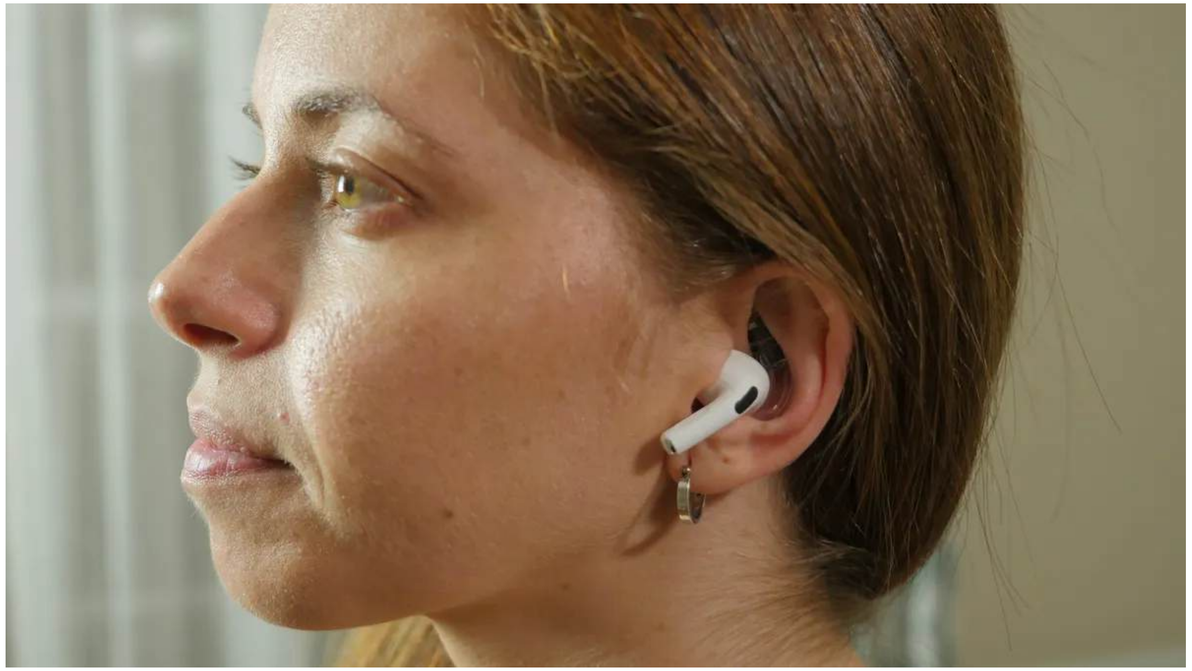
Diagnosing diseases such as Parkinson’s

Tracking injury recovery

Wearables

Allow continuous monitoring

Earables



- Ubiquitous form factor
- Stable location
- Already include inertial sensors for user interaction

Related work

Earable gait analysis

- Work on gait event detection
- Work on step length estimation
- All use a single device

[1] Atallah, Louis, et al. "Validation of an ear-worn sensor for gait monitoring using a force-plate instrumented treadmill." *Gait & posture* 35.4 (2012): 674-676.
[2] Jarchi, Delaram, et al. "Gait parameter estimation from a miniaturized ear-worn sensor using singular spectrum analysis and longest common subsequence." *IEEE Transactions on Biomedical Engineering* 61.4 (2014): 1261-1273.
[3] Seifer, Ann-Kristin, et al. "EarGait: Estimation of temporal gait parameters from hearing aid integrated inertial sensors." *Sensors* 23.14 (2023): 6565.
[4] Seifer, Ann-Kristin, et al. "Step length and gait speed estimation using a hearing aid integrated accelerometer: a comparison of different algorithms." *IEEE Journal of Biomedical and Health Informatics* (2024).

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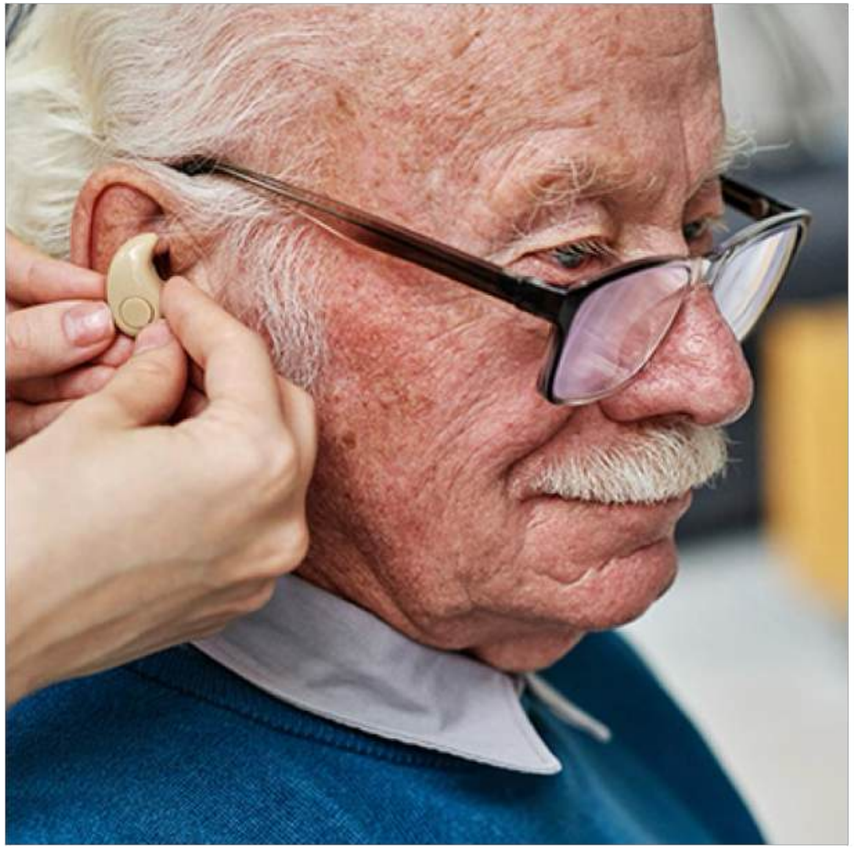
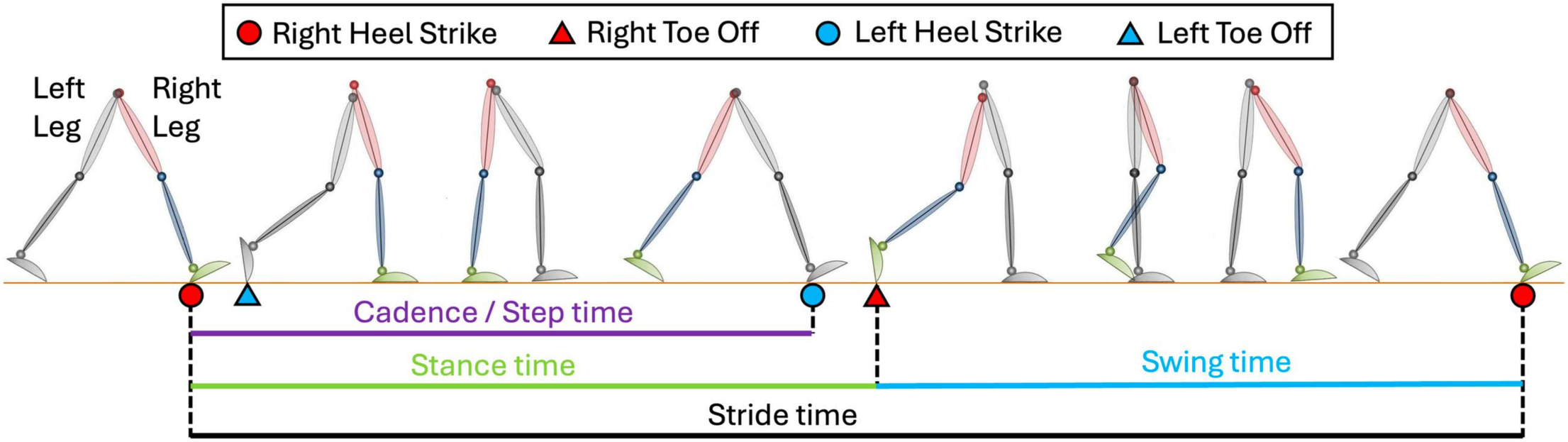
Motivation for WalkEar

Ubiquitous devices already worn by target users



Gait Primer

Temporal parameters



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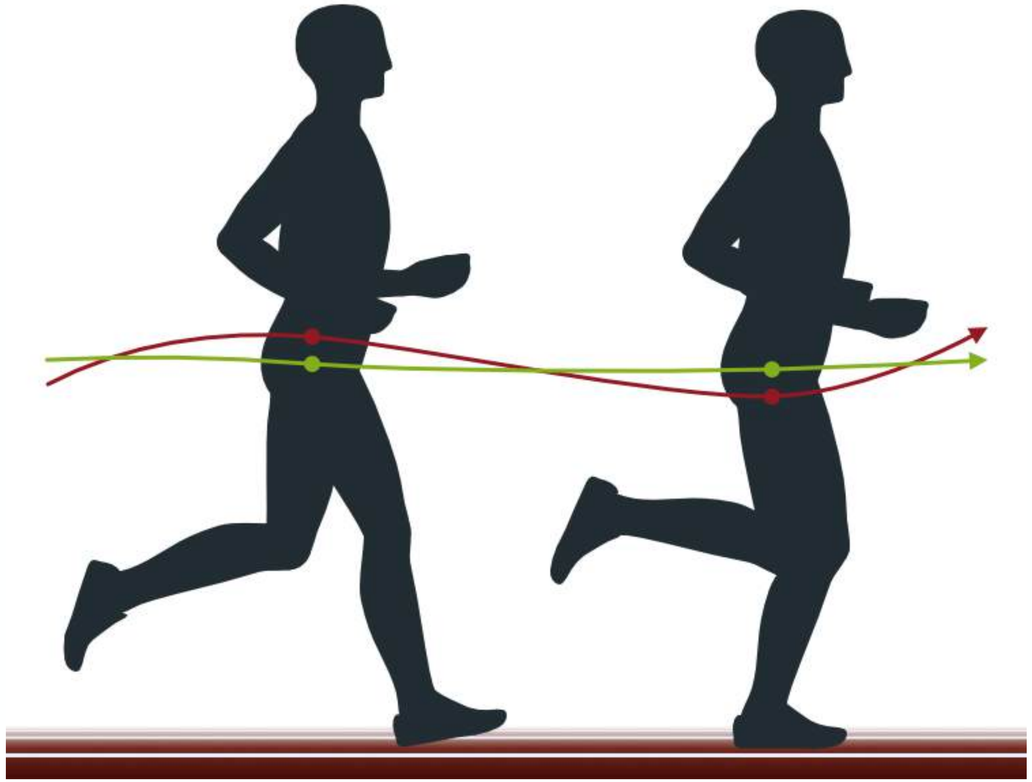
Gait Primer

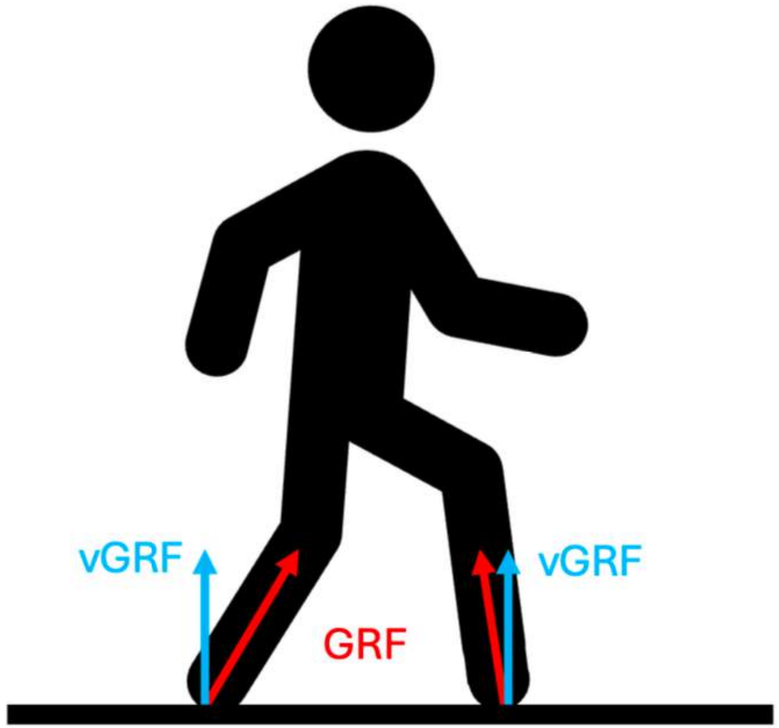
Spatial parameters

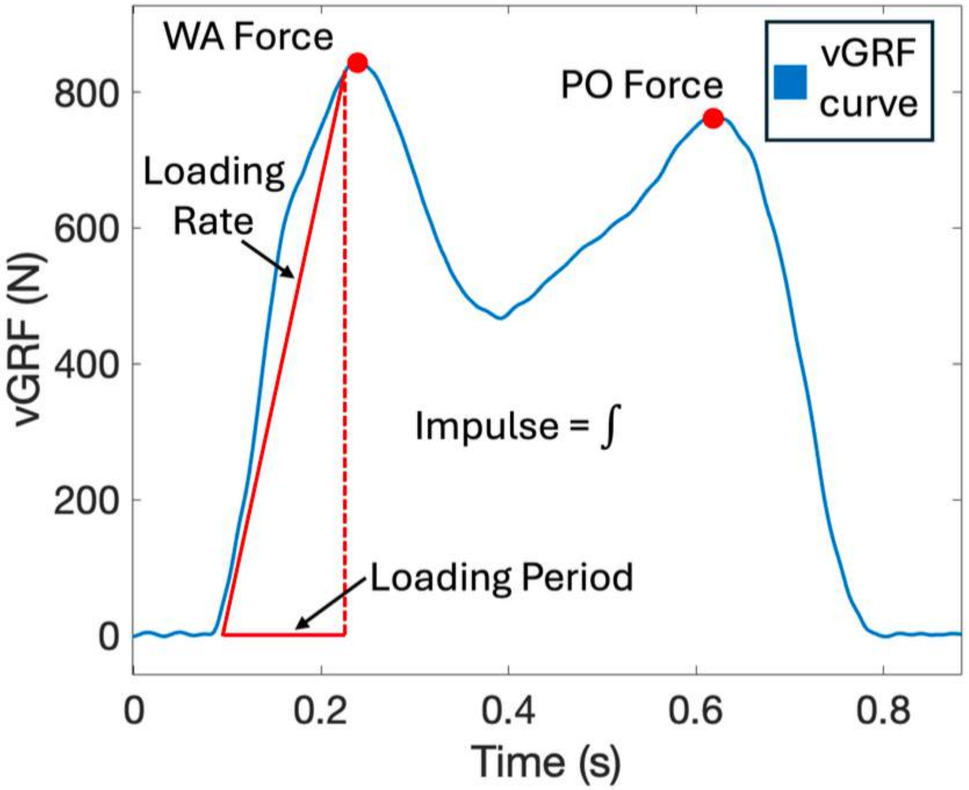


Vertical Displacement

Gait Primer

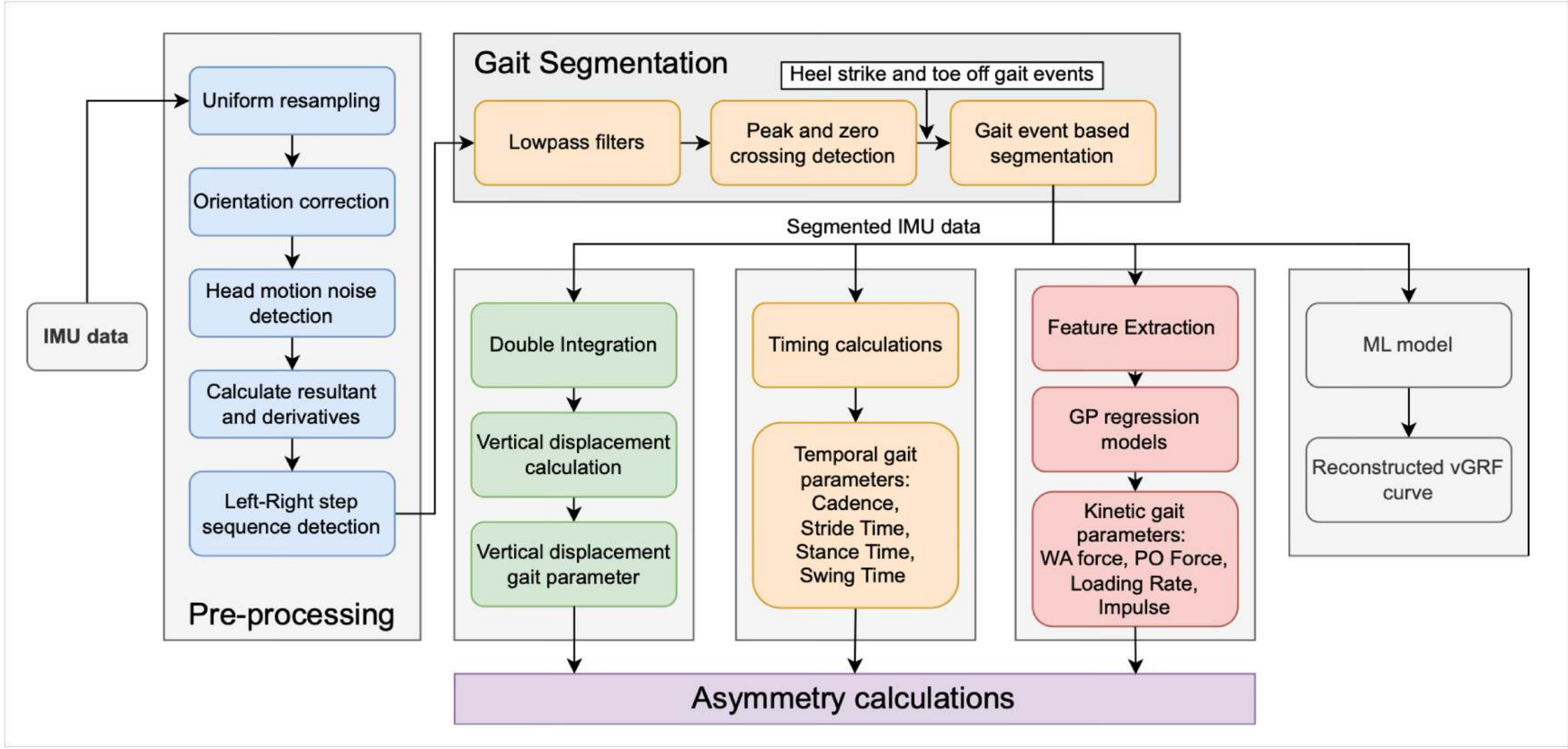
Kinetic Parameters





WalkEar System

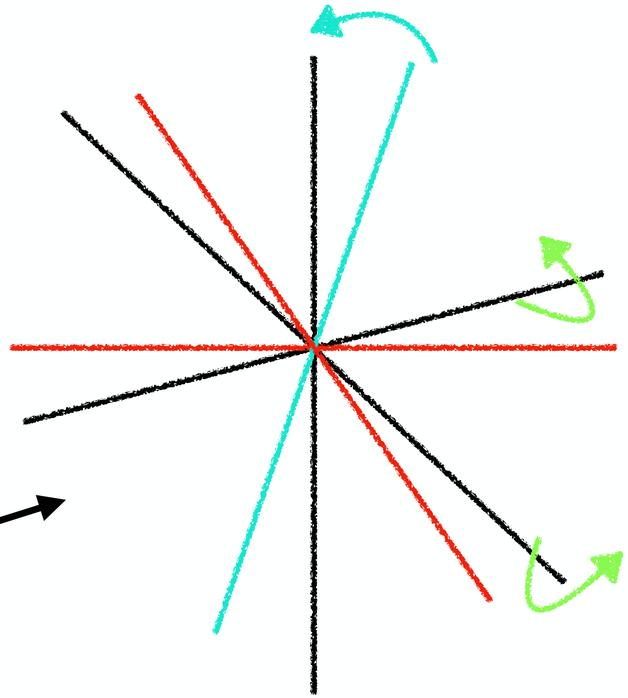
Overview



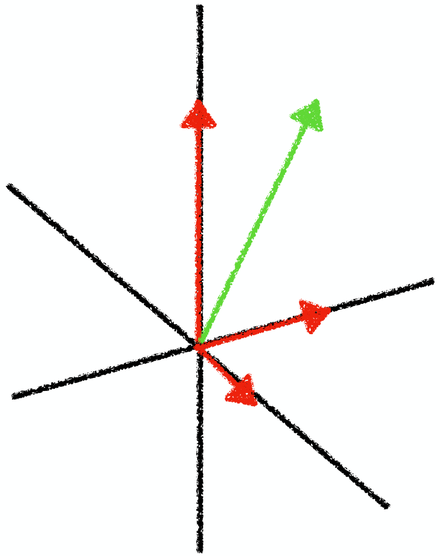
WalkEar System

Preprocessing

- Uniform Resampling
- Gravity Alignment



- Derivatives and resultant



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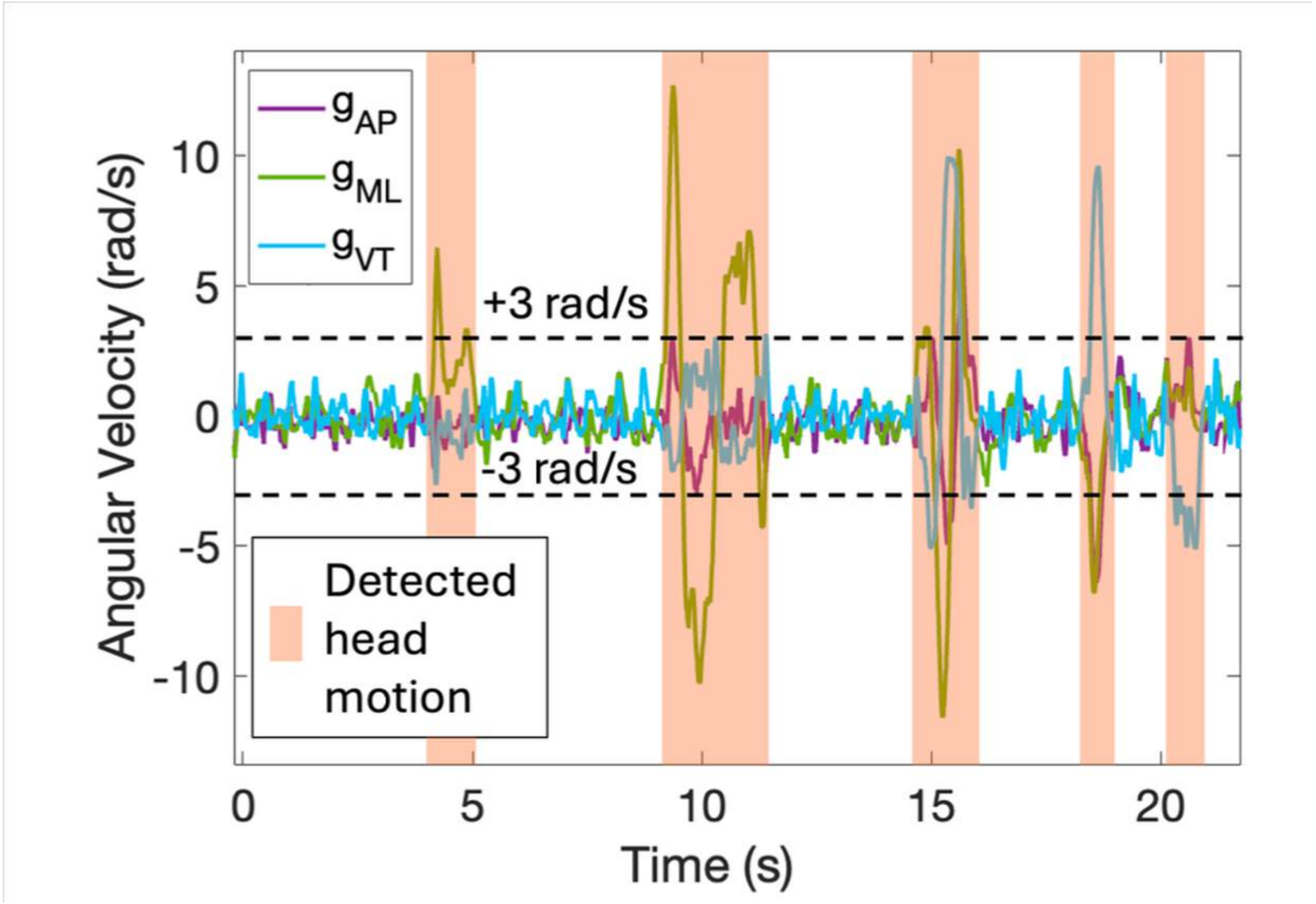
WalkEar System

Noise removal



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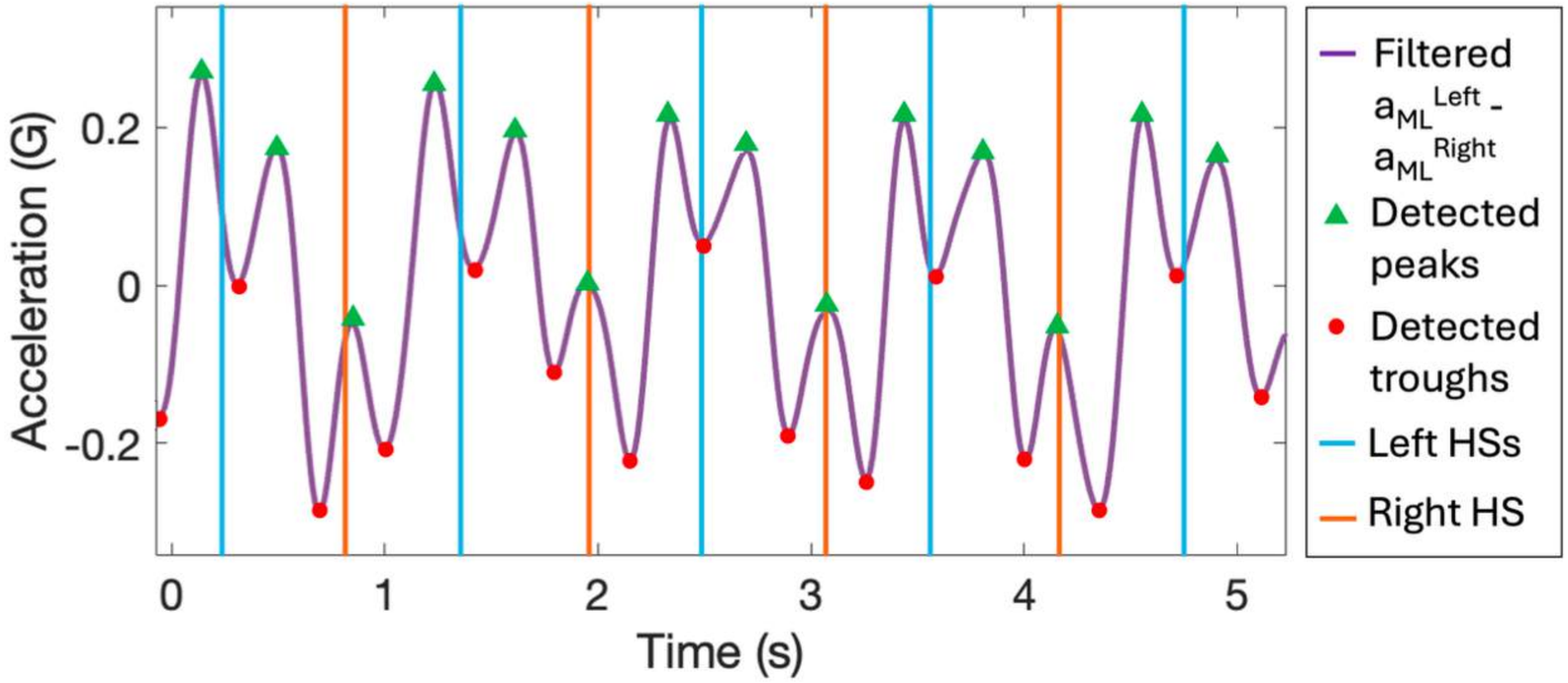
WalkEar System

Left-Right step detection



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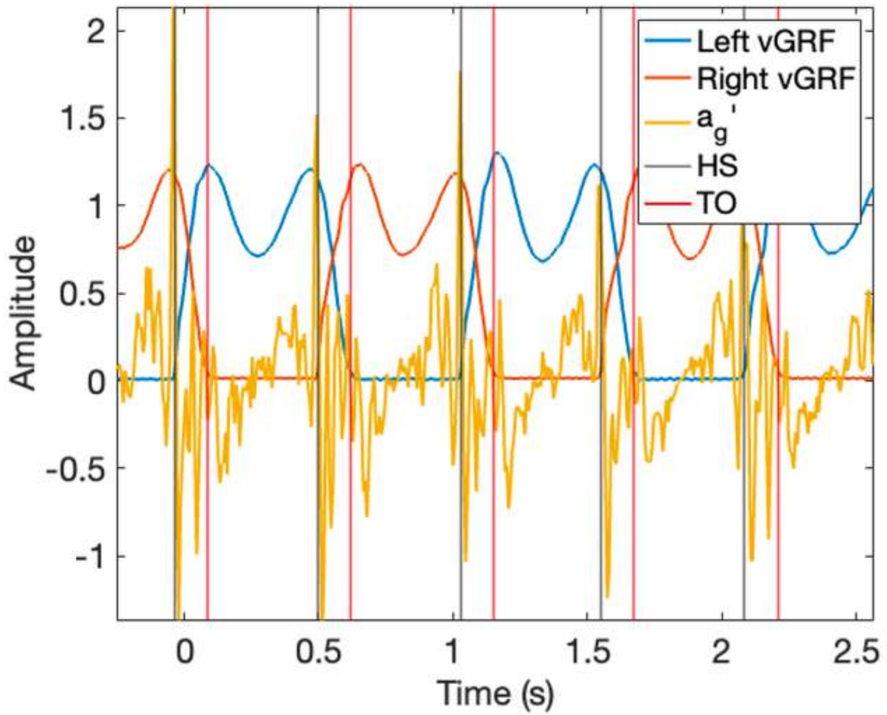
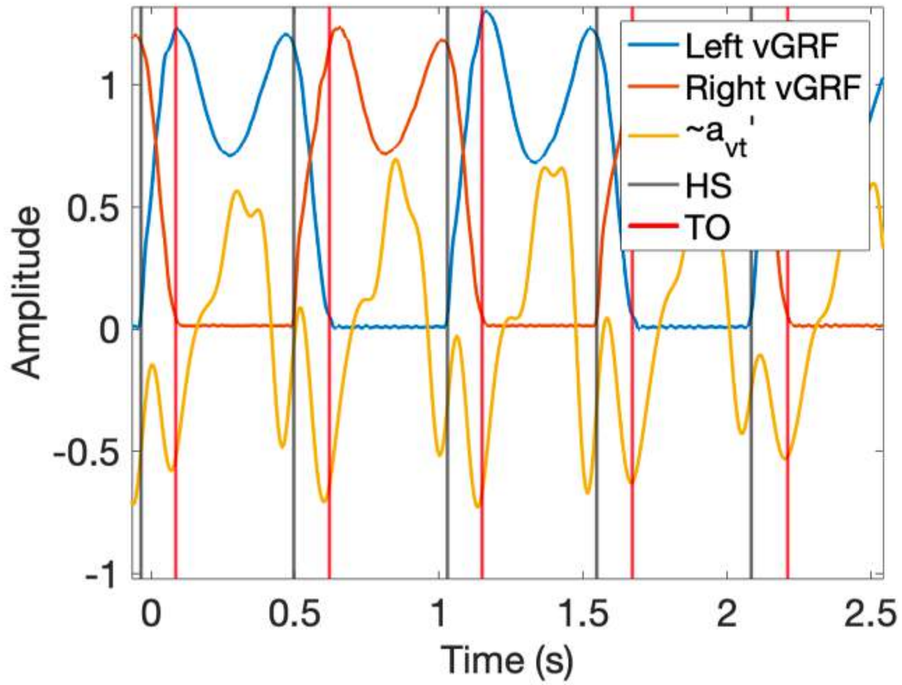
Gait event detection



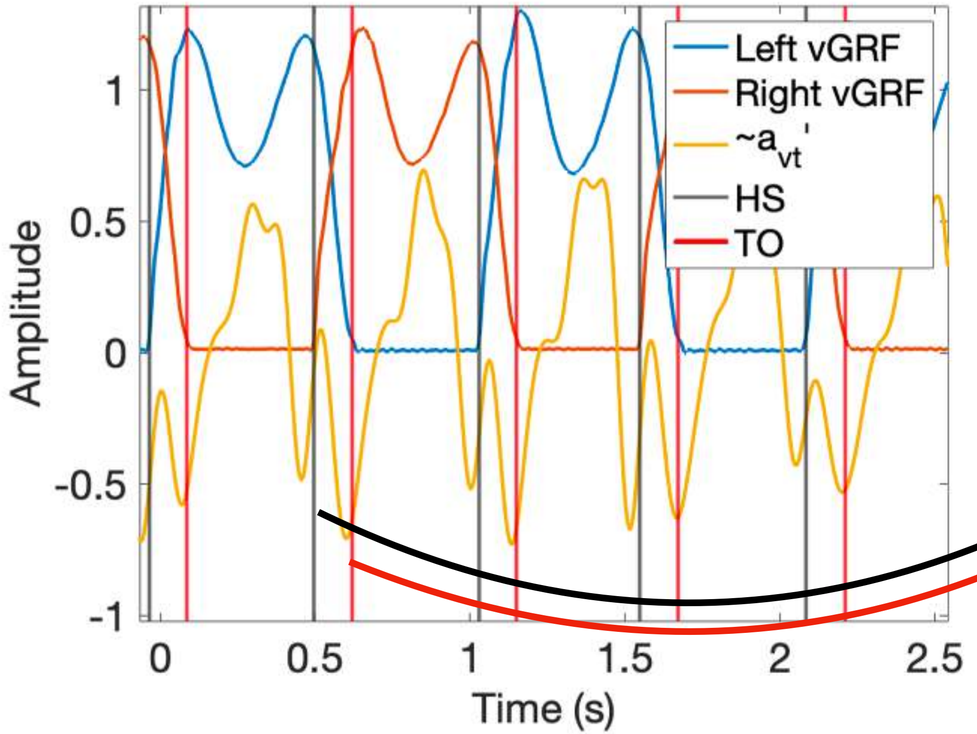
Heel strike detection

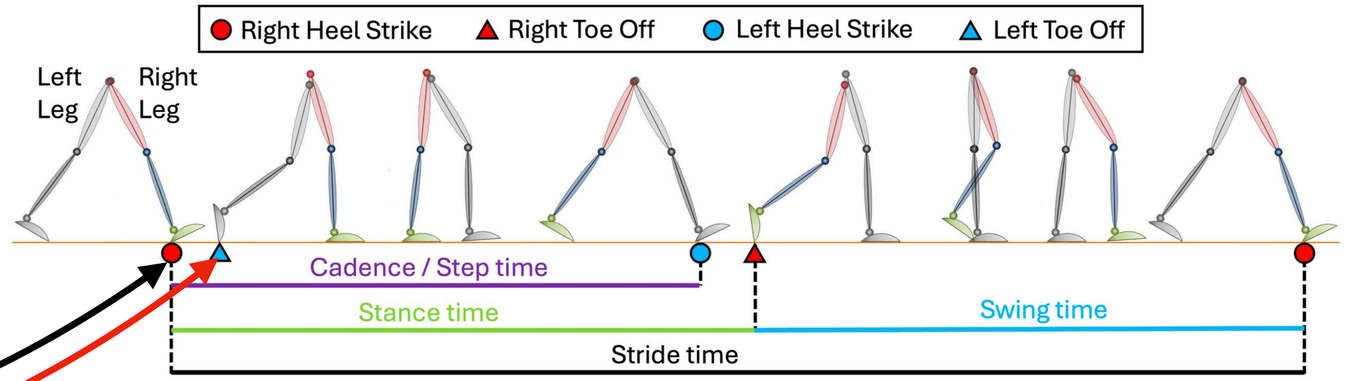


Toe off detection

WalkEar System

Temporal Parameters

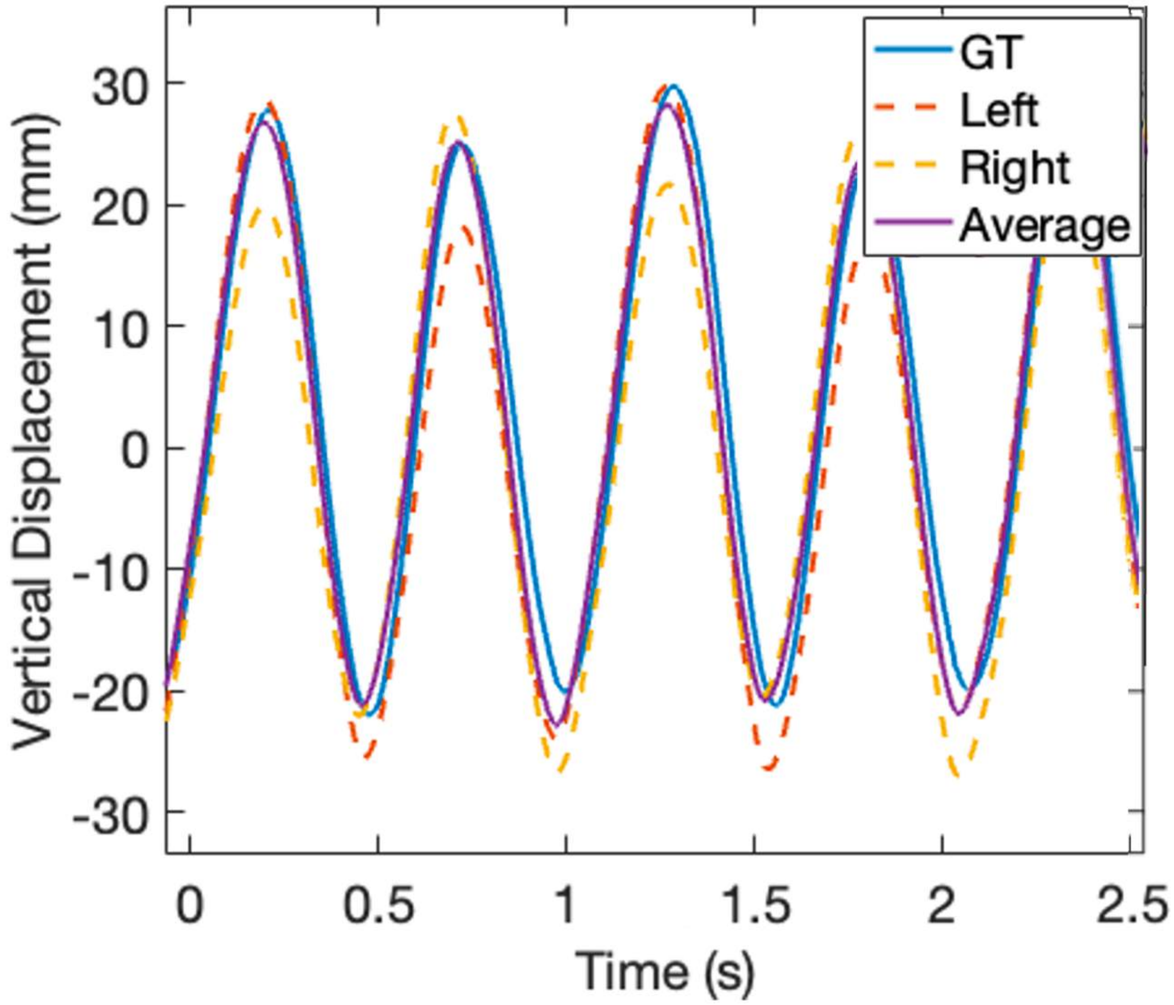




WalkEar System

Vertical Displacement

- Double integration of the vertical acceleration
- Using a high pass filter to remove drift between stages
- Requires good alignment in the vertical direction as well as accurate segmentation to take the step cycle over



WalkEar System

Kinetic Parameters

- Use gait event detection to segment the IMU data
- Resample across segments
- Calculate Features
- GP regression model

Time Domain	Frequency Domain
Maximum amplitude	Band Power
Mean value	Power Bandwidth
RMS value	Peak Amplitude
Shape Factor	Peak location
Crest Factor	Mean Frequency
Clearance Factor	
Impulse Factor	

Features

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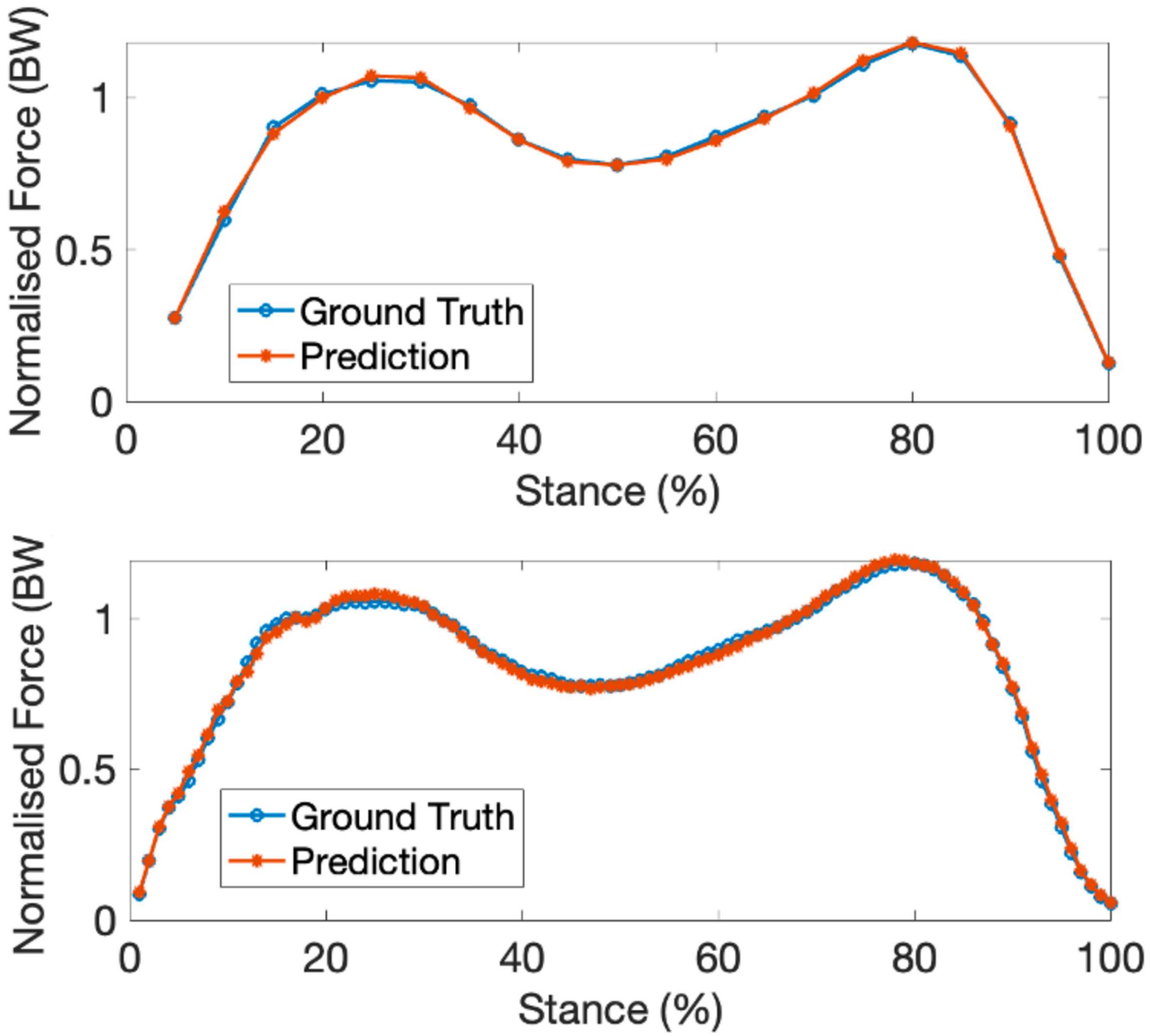
WalkEar System

vGRF Curve Estimation

- Seq-2-Seq regression task
- Using boosted regressors on each sample
- Two models trained, 20 and 100 samples



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WalkEar System

Asymmetries

- Utilising the Left-Right step detection we can calculate LR asymmetry
- This is given as a symmetry index (percentage) a standard measure
- This relies on information being calculated for every step

Data Collection

- 13 healthy Participants
- 2 x 5 min walking
  - Slow and normal speeds
- Free walking validation on force plates

- Additional validation experiments:
  - Different shoes
  - Stop and Go

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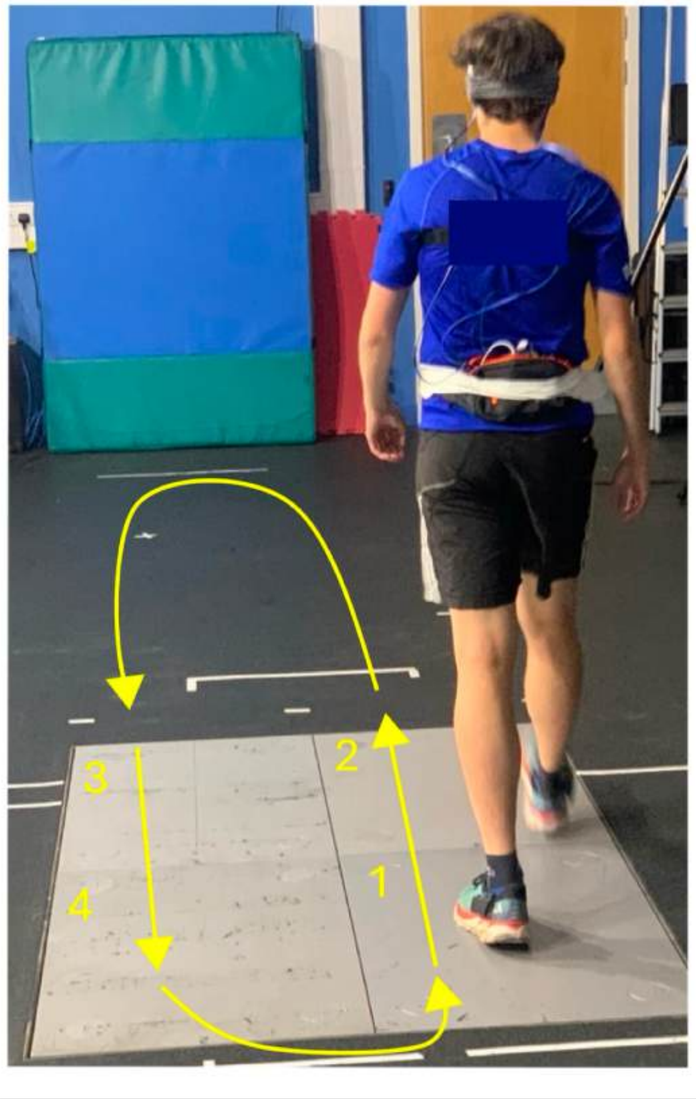

Results

Overall

Metric	Cadence step/min	Stride Time s	Stance Time s	Swing Time s	VD mm	WA Force N	PO Force N	Loading Rate N/s	Impulse Ns
MAE	2.47	0.0114	0.0216	0.0215	1.93	17.5	8.59	328	2.26
SDE	4.55	0.0214	0.0313	0.0314	2.51	23.2	11.3	491	3.59
MAPE	2.06%	1.02%	3.10%	5.14%	2.72%	2.12%	1.34%	3.74%	0.73%
ME	-0.21	-0.00014	-0.00694	0.0067	0.94	2.69	-0.087	-105	-0.24

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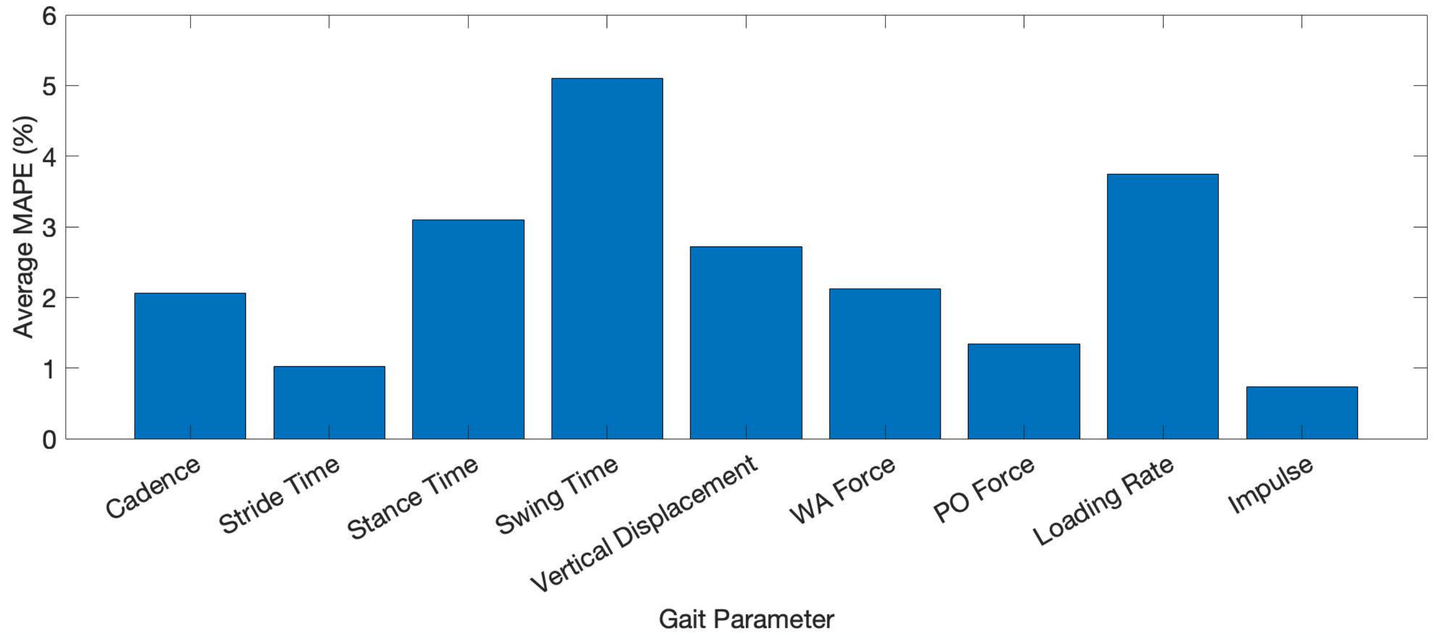

Results

Comparison with related works

- Beating or comparable to baselines for tasks on earable devices

Parameter	Ours	e-AR [28], [29], [14]	EarGait [15] Reported	EarGait [15] Our Dataset
Cadence MAE	2.47	8.88	**1.85**	1.93
Stride time MAE	**0.011**	0.028	0.012	0.015
Stance Time MAE	**0.022**	0.038	0.076	0.064
Swing Time MAE	**0.022**	0.036	0.078	0.067
WA force (R^2)	**0.69**	0.35	-	-
PO Force (R^2)	**0.65**	0.36	-	-
Loading Rate (R^2)	**0.73**	-	-	-
Impulse (R^2)	**0.69**	0.26	-	-

- For vGRF curve estimation WalkEar is comparable to foot and trunk located devices

Validation Method	NRMSE			Correlation		
	Ours (20)	Ours (100)	[24]	Ours (20)	Ours (100)	[24]
LOSO	5.25	5.12	-	0.985	0.983	-
5 Fold CV	**2.23**	**2.30**	7.15	**0.995**	**0.996**	0.97
Individual	8.67	8.67	**1.7**	0.958	0.958	**1.00**

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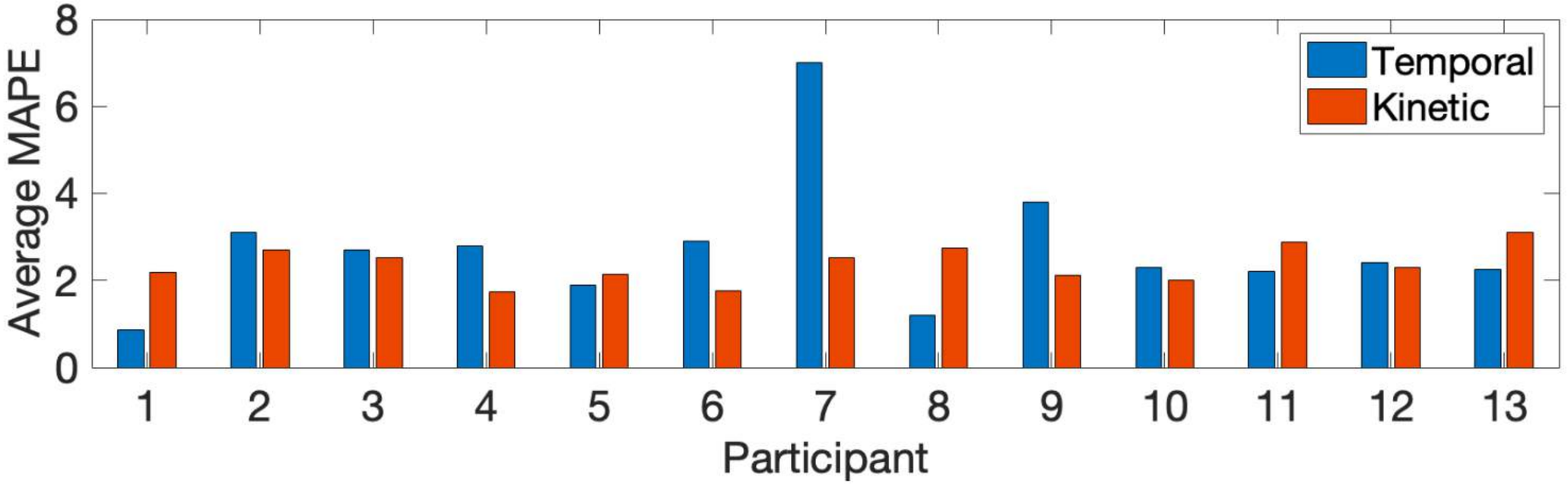
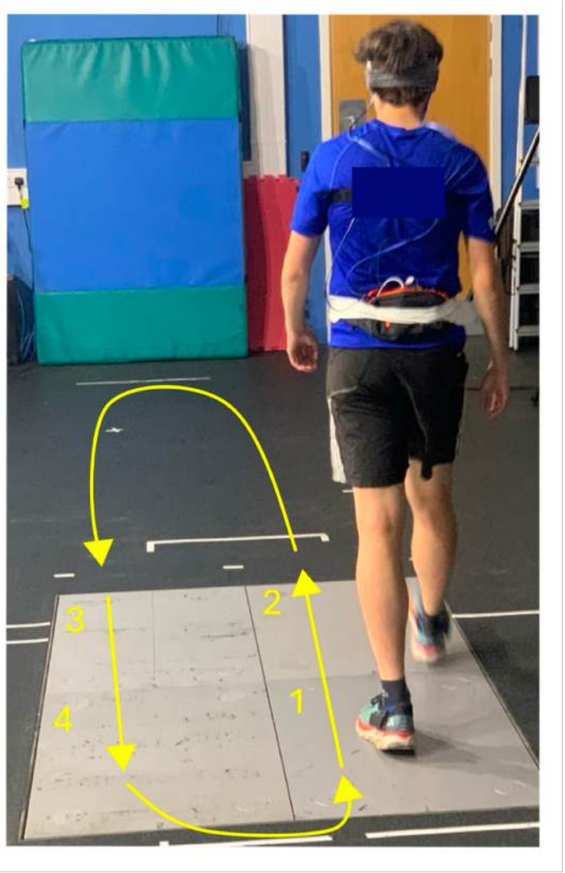
Results

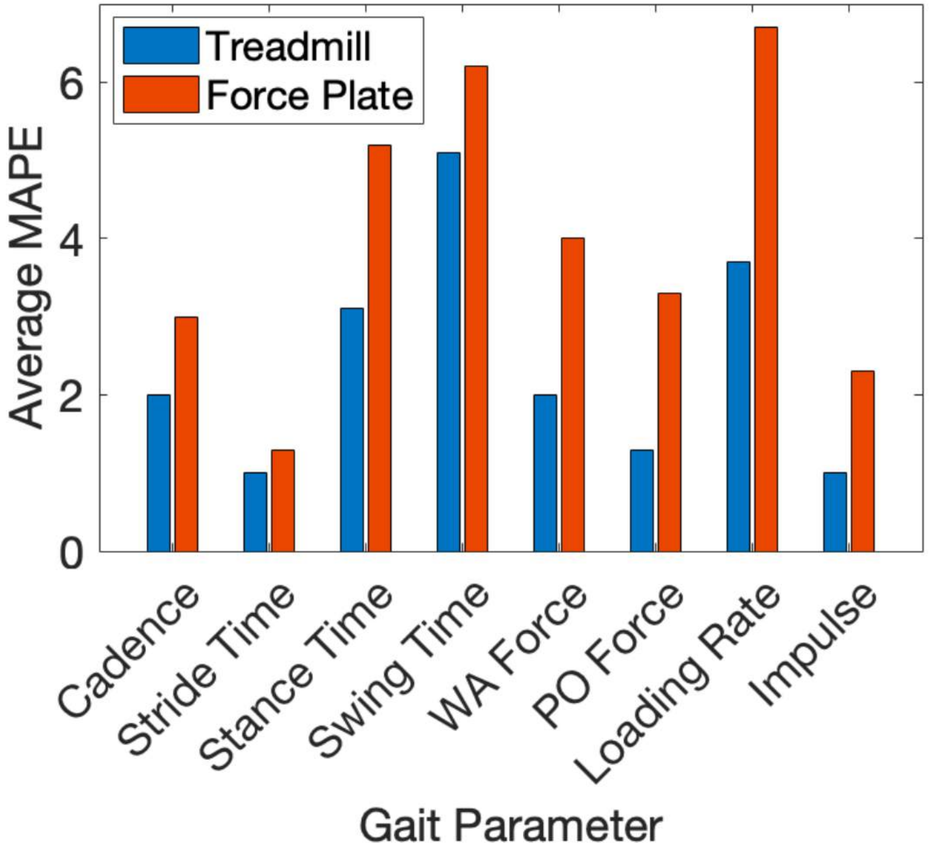
Per Participant



Results

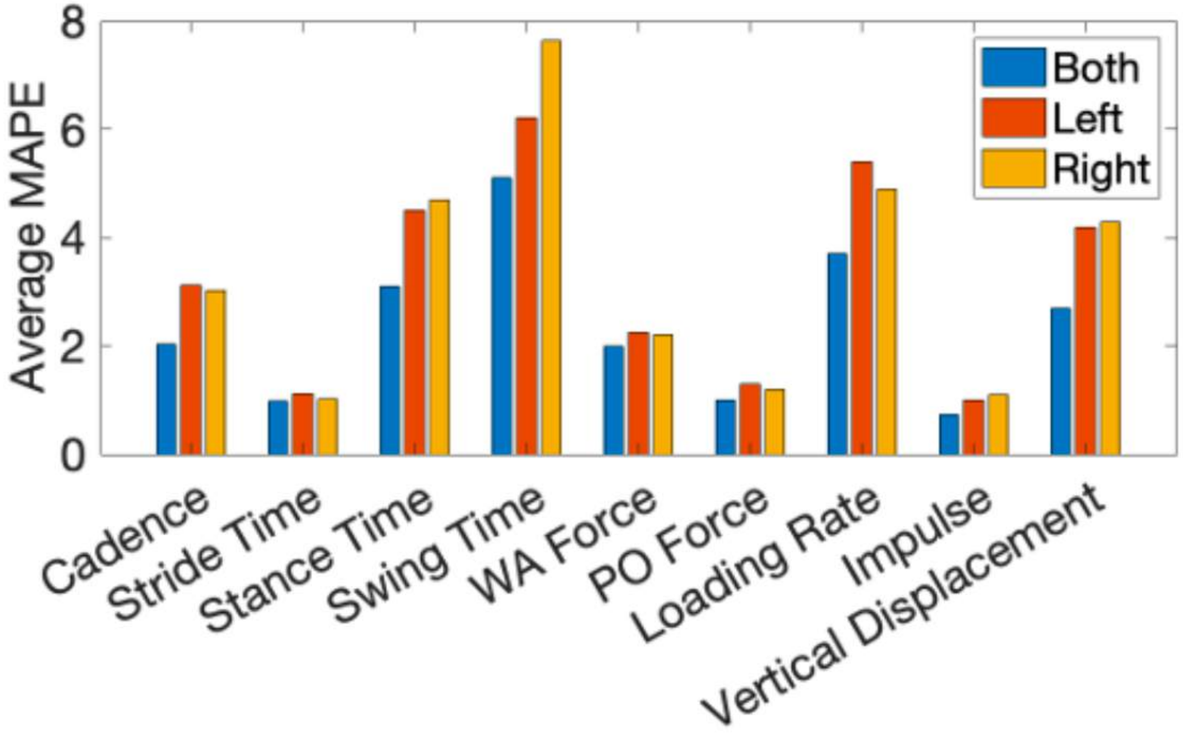
Free walking setting





Results

System benchmarks - Left + Right Devices and Sampling Rate



Sample rate	150 Hz (original)	100 Hz	50 Hz	20 Hz
Cadence	2.06%	2.12%	2.46%	3.84%
Stride time	1.02%	1.06%	1.11%	1.75%
Stance Time	3.10%	4.35%	5.52%	7.59%
Swing Time	5.14%	6.34%	7.82%	9.27%
WA force	2.12%	2.91%	3.14%	4.80%
PO Force	1.34%	1.95%	3.14%	4.76%
Loading Rate	3.74%	4.85%	5.43%	6.51%
Impulse	0.73%	1.42%	1.99%	2.89%

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Results

On-device performance

- WalkEar was implemented on an iPhone 15

Algorithm stage	Battery consumption in 30 minutes (%)	Latency (ms)
Preprocessing and Timing	2%	0.006
Kinetic	3%	65.7
vGRF (20 samples)	10%	328.5
Spatial	2%	0.012
Overall	12%	394.22

- We also tried smaller linear models showing space for improvements with minimal accuracy loss

Future work

- Generalise to running.
- Test more complex daily living scenarios.
- Clinical validation.

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Conclusions

- WalkEar uses lightweight techniques for gait parameter estimation.
- First time showing vGRF curve reconstruction from the ear and showing improved accuracy on other tasks such as gait event detection.
- Set the potential for future clinical work by getting initial results on important health markers.

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Conclusions

- WalkEar uses lightweight techniques for gait parameter estimation
- First time showing vGRF curve reconstruction from the ear
- Set the potential for future clinical gait work with earables

Any Questions?

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