

TORUS-53: A Wearable Infrastructure for Longitudinal Residential Movement Monitoring

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Abstract—The use of Internet of Things (IoT) sensors within the home is expected to provide benefits, such as the ability to monitor symptoms throughout the day and in a stress-free real-world context. For Parkinson’s disease, where motor symptoms fluctuate and are expressed through everyday activities, this requires sensing systems that can capture body movement continuously and reliably without constraining natural behaviour. In this paper, we describe the TORUS wearable subsystem, part of the TORUS domestic heterogeneous sensor installation intended to support assessments of Parkinson’s symptoms in the home. We demonstrate the system’s reliability, coverage and goodput by a comprehensive characterisation study, and show an example usage of the system on the detection and characterisation of stair activities in a real-world residential environment.

Index Terms—Internet of things, Bluetooth Low Energy, Wearable sensors, Activity recognition

I. INTRODUCTION

Parkinson’s disease (PD) is a neurological disorder with over 160 000 people diagnosed with the disease in the UK as of 2025 [1]. PD is characterised by motor impairments including bradykinesia, rigidity and tremor [2], as well as a wide range of non-motor symptoms, such as sleep disturbances [3]. Healthcare traditionally relies primarily on relatively episodic observations by clinicians to assess patients’ wellbeing and symptoms. This model, however, does not provide a complete picture for PD since symptoms vary widely between People with Parkinson’s (PwP) as well as fluctuating throughout each day. Thus, not only may various professionals be involved in PD care and symptom monitoring [4], but importantly the PwP themselves and their family or companions may also engage actively in tracking their symptoms, to better understand their own condition and how it responds to medication, and to provide an improved evidence base for working with their clinicians. As Williams et al. [5] characterise the desired outcome, ‘the patient and the doctor together are the expert’.

However, while a valuable approach and helpful in gaining insight, self-monitoring has known limitations. A 2023 survey found that while clinical staff frequently recommended that the patient record at least some information about the course of symptoms, only around one-third of PwP participating in the survey had done so over the past year. Some reported practical

difficulties such as finding the approach overly time-consuming or tiring, or, learning that the clinical picture was relatively stable, finding it difficult to find motivation to continue over time [4]. Therefore, sensor technology holds the potential to provide helpful supporting information, such as longitudinal objective measurement of movements and symptoms.

Several sensor technologies have been developed by the research community. Wearable devices with inertial measurement units (IMUs) [6] and complementary sensors [7] are developed targeting various body locations such as thigh, waist and wrist [8, 9, 10]. Such devices are often powered by a battery and therefore low-power consumption is a critical requirement for longitudinal measurements. To transmit sensor data, typical wireless protocols such as Bluetooth Low Energy (BLE) and IEEE 802.15.4 are commonly used. However, legacy BLE advertising is constrained by the throughput [11] when high sample rate is required by IMUs (e.g. 50 Hz to 200 Hz) for downstream biomechanical movement analysis [12]. IEEE 802.15.4 supports the integration with TCP/IPv6 via the 6LoWPAN adaption layer, but the supported bitrate still does not satisfy our requirement, and it requires a dedicated networking stack and gateway infrastructure [13], which increases deployment cost and maintenance complexity.

With the recent advancements in BLE extended advertising, characterisations in a controlled environment demonstrate significantly higher throughput [11], higher reliability [14] and lower power consumption [15]. However, such characterisations are not fully verified in a real-world deployment, such as in a residential setting. To address these challenges, this paper presents the TORUS wearable subsystem. It combines a multi-sensor wearable device and a distributed network of fixed commercially-available receivers, utilising BLE extended advertising to achieve high-sensor rate data communication. We demonstrate the system’s robustness and reliability in a residential environment via a scripted experiment.

II. SYSTEM DESCRIPTION

The TORUS system (Figure 1) is a heterogeneous sensor network designed to collect information from a wearable device (including an IMU and a barometric pressure sensor) and computer vision sensors. The wearable device is able to continuously capture movement-related [16] and sleep-related [17] signals in free-living settings, while video-based

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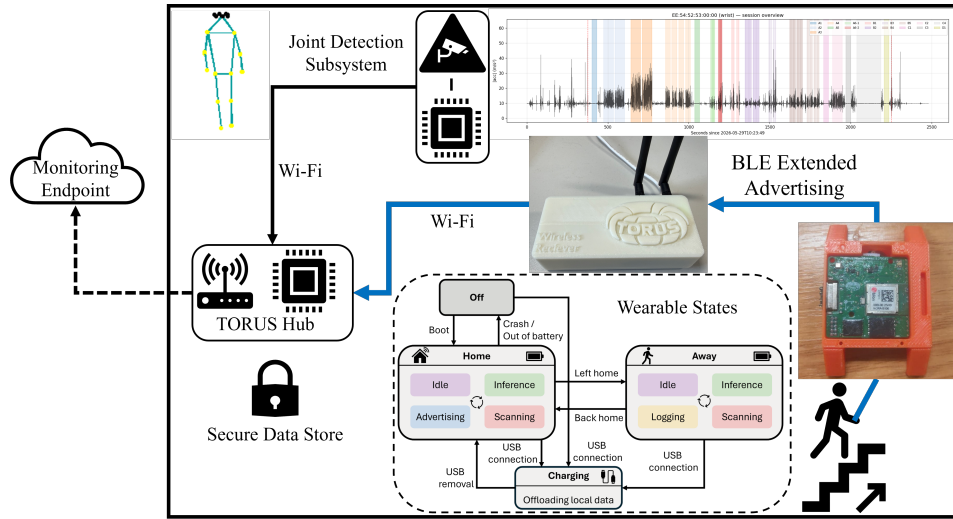


Figure 1. High-level architecture of the TORUS system, including video joint detection (above) and wearable data collection (lower right, highlighted in blue). Possible wearable states are: Off, Home, Away and Charging (inset, lower centre).

joint detection has the potential to detect further features relating to quality of movement and activities of daily living (ADL). In this paper we focus on characterising the wearable network of the TORUS system, illustrating its successful use in the context of a common ADL – climbing stairs.

The TORUS wearable device equips two sensors: a BMI270 6-axis IMU sensor (accelerometer range: ± 8 g, gyroscope range: ± 500 dps, sample rate: 100 Hz) and a BMP390 barometric pressure and temperature sensor (resolution: ± 0.9 Pa, sample rate: 12.5 Hz). The device is controlled by an nRF5340 system-on-chip (SoC) and is powered by a 3.7 V 220 mAh lithium-polymer battery. An empirical measurement yielded a battery life of 57.17 hours. It supports BLE extended advertising at a maximum TX power of +3 dBm. It has four operating states: Off, Away, Home and Charging. As the experiments in this work are conducted in a residential setting, the device autonomously operates primarily in the Home state, during which it continuously transmits sensor data via BLE at +3 dBm, and this state is therefore the focus of the evaluation.

To receive BLE extended advertisements from the wearable, fixed receivers are equipped with an Intel® AX210 wireless adapter, managed by a Raspberry Pi 5 single-board computer. A receiver has the following three functions. First, it passively scans for wearable BLE packets at 100% duty cycle and decrypts them using a shared encryption key. Second, it envelops sensor data into a structured JavaScript Object Notation (JSON) packet and forwards it to the TORUS Hub via Message Queuing Telemetry Transport (MQTT). Third, it periodically broadcasts a heartbeat signal for the wearable device to confirm its presence in the instrumented environment, acting as the trigger for Home/Away state transition.

Monitoring in the home raises privacy and security concerns, which we address in part through privacy-and security-by design practices [18]. The former includes suitable technical and organisational access controls to data and appropriate measures,

such as data masking and aggregation where suitable. The latter include AES-CTR-128 encryption in data transmission and LUKS-based disk encryption to secure data at rest. We also prioritise transparency and clarity to support meaningful informed consent, and work actively with PwP via our Patient Council to ensure that the views of potential participants are taken into account.

III. EXPERIMENTAL DESIGN

A. Stair Activity Protocol

Stair negotiations are important ADL and difficulties negotiating stairs can result from a range of different factors, such as lower limb strength and balance etc. [19]. Various parameters may be identified to characterise stair activities, such as walking speed on stairs, assessment of handrail use and proximity to the rail. Additionally, specific stair negotiation strategies may be detected, such as stair climbing ‘foot over foot’ (FOF) (e.g. one foot per step) or ‘two feet per step, or both each step’ (BES), which is to say, placing both feet on each step before continuing to the next step [20], or sideways placement of one’s body to face the railing. These compensatory stair walking strategies may indicate strength deficits, limited range of motion or poor balance [21, 22], as well as low confidence [23]. Conway et al. [24] found that PwP stair climbing speed is lower than that of control participants, while Roth et al. [21] indicate that a small subset of participants with PD who had been identified to be at greater fall risk with the BES strategy in negotiating stairs.

We therefore developed a scripted protocol targeting four stair negotiation patterns: normal stair use, slow stair use, stair use with handrail and BES. Before and after these stair sessions, the protocol also included general mobility-related activities commonly used in the assessment of PwP, including plain walking, sitting, turning, sit-to-stand transitions, and lying. The experiment was conducted in a residential house located at Bristol, UK, using a staircase comprising 10 steps, each with a

riser height of 16 cm. Seven healthy control participants were recruited. Each participant performed each stair negotiation pattern twice while wearing four TORUS wearable devices, positioned on the dominant wrist, both ankles and the lower back at approximately the L4 level. Although future residential deployment is intended to use a single wrist-worn device, additional devices were included in this study to stress-test the proposed infrastructure under simultaneous high-rate streaming and to support future sensor-placement ablation studies for stair negotiation analysis. The present work focuses primarily on the former aspect. This study has been approved by the University of Bristol Faculty of Engineering Research Ethics Committee, reference 21685.

B. Network Characterisation

Network performance was characterised from the BLE advertisement logs recorded by the receivers. Since the same advertisement could be received by multiple receivers, system-level performance was assessed after deduplicating advertisements across receivers. A *unique packet* was defined by the wearable identifier and packet identifier. When the same packet was received by multiple receivers, its system-level arrival time was taken as the earliest receiver timestamp. Four metric groups were evaluated: reliability, coverage, timing, and goodput.

a) *Reliability*: Packet delivery was estimated relative to a modelled theoretical maximum packet count. For a wearable in a session of duration T_s , defined as the interval between its first and last received packet, the device performs $N_{hb} = \lfloor T_s/T_{hb} \rfloor$ heartbeat scans as introduced in Section II. Each heartbeat scan introduces an advertising downtime of T_d , during which device's advertising are replaced by scanning. The expected number of unique packets within such session is therefore

$$P_{exp} = \left\lfloor \frac{T_s - N_{hb}T_d}{T_p} \right\rfloor \quad (1)$$

with $T_p = 120$ ms as the BLE advertising interval, $T_{hb} = 60$ s and $T_d = 1.25$ s. All three parameters are configurable to match different levels of responsiveness and the required data throughput. The packet delivery ratio is $PDR = N_{rx}/P_{exp}$ for N_{rx} received unique packets. For each body site (wrist, ankles, lower back), we report the mean and standard deviation (SD) of PDR across the seven sessions. Additionally, system-level PDR was calculated from the union of packets received by any receiver, thereby quantifying the effective delivery performance of the multi-receiver infrastructure.

b) *Coverage*: For each received advertisement, the receiver signal strength indicator (RSSI) was extracted. RSSI was summarised at the room level. We computed the mean RSSI for each session and then reported the mean and SD across sessions. Due to the multi-receiver topology design, it is also important to understand the redundancy of the network. Therefore, reception diversity was quantified as the number of distinct receivers, n_{rx} , that received each unique packet. We report the distribution of n_{rx} and the proportion of packets received by at least two receivers. This metric captures the level of spatial redundancy in the receiver network and indicates

Table I
CROSS-SESSION DELIVERY PERFORMANCE BY BODY SITE ($n = 7$). PDR: MEAN $\pm$ SD ACROSS SESSIONS AND POOLED, IAT: MEDIAN INTER-PACKET INTERVAL, JITTER: SD OF BACK-TO-BACK INTERVAL ON DEVICE VS. RECEIVER CLOCK.

Body site	PDR (%)		IAT (ms)	Data jitter (ms)	Delivery jitter (ms)
	mean $\pm$ SD	pooled			
wrist	72.9 $\pm$ 7.1	74.0	126	0.7	24.6
lower back	73.9 $\pm$ 3.7	74.1	126	2.1	27.8
left ankle	56.6 $\pm$ 10.4	59.1	127	1.3	28.2
right ankle	71.5 $\pm$ 6.4	72.7	126	1.6	27.1
System	70.0		531 594 packets, 6.7 h		

the extent to which the system is robust to packet loss at any single receiver.

c) *Timing*: Packet timing was characterised using the packet inter-arrival time (IAT), defined as the time difference between consecutive packet arrivals at the receiver. Jitter was then evaluated only for back-to-back packet pairs, defined as consecutive packets whose packet identifier differed by exactly one. This excludes intervals affected by packet loss or heartbeat gaps. Two jitter measures were computed. Delivery jitter was defined as the SD of the delivered IAT, while data jitter was defined as the SD of the wearable device-clock interval between the first IMU samples in consecutive packets. Comparing these two quantities separates variability introduced by BLE scheduling and reception from variability in the underlying sensor data timing.

d) *Goodput*: Goodput was estimated from the wearable firmware-defined sensor sample rate and the measured packet delivery ratio (PDR). For each wearable, the configured rate was calculated as $R_{cof} = 8Lf_p$, where $L = 225$ B is the on-air payload length and $f_p = 1/T_p$ is the estimated packet transmission frequency. This corresponds to approximately 13.85 kbit/s per wearable. Delivered goodput was calculated as $R_{del} = R_{cof} \cdot PDR$ and reported both per wearable and for the four-wearable configuration, with aggregate goodput estimated using the system-level pooled PDR.

IV. RESULTS AND DISCUSSION

A. Network Performance

The reliability and timing characterisation results were reported in Table I. Over seven sessions with a total duration of 6.7 hours, a total of 531 594 packets were received, yielding an overall PDR of 70 % for the four-wearable configuration. Wearable devices at wrist, lower back and right ankle achieved average PDR above 70 %, which was relatively consistent across participants. Left ankle device, in comparison, had a poor signal performance for reliable data delivery. Its high SD on PDR across sessions suggests inconsistent delivery performance. This is attributed to a hardware manufacturing deficiency. Its PCB underwent a rework procedure to replace the malfunction SoC part that integrated the wireless antenna. This rework could cause damages to the ground copper, which would significantly affect the antenna performance.

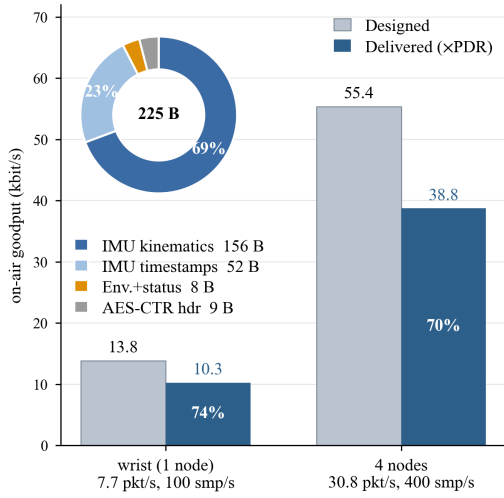


Figure 2. Composition of a single on-air advertisement payload and achieved goodput for the single- and four-wearable configuration.

However, such deficiency does not affect sensor data timing and delivery timing. All four sensors achieved an IAT in the range of 120–130 ms. This within-10 ms delay on top of the configured BLE advertising interval of 120 ms is randomly added to each advertisement by the controller to avoid packets collisions following the Bluetooth specification. Data jitter and delivery jitter also demonstrate great wearable internal clock and receivers clock consistency. Understanding such timing consistency in a multi-sensor and multi-receiver network helps any sensor fusion algorithms that requires synchronisation.

IMU-related data occupies 92 % of the 225 B payload as shown in Figure 2. This is achieved by batching 13 IMU samples into a single advertisement. The value of 13 is not arbitrary, but is the largest batch size that fits within a single advertising protocol data unit (PDU) while retaining the other system fields. Although BLE extended advertising supports packet chaining [14], this mechanism is not used in the proposed system. Chained extended advertising relies on the AuxPtr field to direct the receiver to subsequent chained fragments, creating a sequential dependency between PDUs. In an RF-noisy indoor residential environment, and because BLE advertising is an unacknowledged best-effort broadcast mechanism rather than a guaranteed-delivery transport, loss of an AuxPtr-bearing PDU can break the chain and render the remaining fragments unrecoverable. Packet chaining may therefore amplify individual packet losses into extended data gaps, which may compromise downstream analysis. Such vulnerability has already been observed even in a controlled environment [15]. With single PDU extended advertising, the proposed system achieved a goodput of 10.3 kbit/s and 38.8 kbit/s for the single- and four-wearable configuration in the residential environment. Compared with legacy BLE advertising, which has a theoretical maximum throughput of approximately 11.6 kbit/s only at a 20 ms advertising interval, the use of extended advertising allows a 120 ms interval for a comparable single-wearable throughput. This corresponds to a

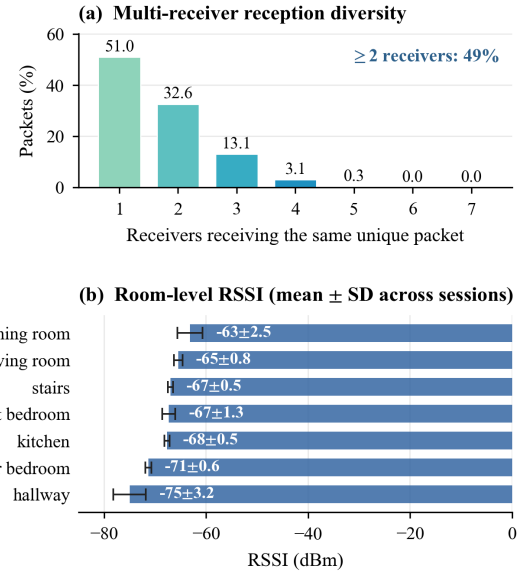


Figure 3. Characterisation of system network coverage represented by receiver diversity and room-level RSSI.

6 times reduction in advertising interval, increasing sleep time for CPU and radio, thereby supporting low-power operation. Conversely, at the same 120 ms advertising interval, legacy advertising would provide only approximately 1.93 kbit/s, which is about 5.3 times lower than the proposed single-wearable goodput and insufficient for the high-sample-rate IMU payload targeted in biomechanical movement analysis [25].

To demonstrate the coverage of the proposed system, Figure 3 presents receiver redundancy and RSSI per room. The room-level RSSI ranged from -63.0 ± 2.5 dBm in the dining room to -75.0 ± 3.2 dBm in the hallway. Since all rooms remained more than 15 dB above the nominal BLE receiver sensitivity of approximately -90 dBm, the packet loss reported in Table I is unlikely to be explained by insufficient radio coverage alone. Instead, the dominant limiting factors are more likely to be medium-access contention between concurrently advertising wearables and body shadowing during the scripted protocol.

Coverage was also stable across sessions. The between-session SD was no greater than 0.8 dB in most rooms, for example -67.0 ± 0.5 dBm on the stairs and -68.0 ± 0.5 dBm in the kitchen. This indicates that the fixed receiver placement provided stable, participant-independent coverage without requiring per-user calibration. The larger variability observed in the hallway and dining room, with SDs of 3.2 dB and 2.5 dB, respectively, is consistent with the use of these rooms as transient or free-seating spaces, where RSSI depends more strongly on the wearer's instantaneous position.

Receiver redundancy further contributed to system reliability. Overall, 49 % of unique packets were captured by two or more receivers. The mean number of receivers per packet was 1.7, while the remaining 51 % of packets were captured by a single receiver. Combining receptions across receivers therefore improves robustness to transient body shadowing,

local RF fading, and single-receiver failure. It should be noted, however, that RSSI is available only for successfully received packets and that the degree of receiver diversity depends on receiver density, which varied between deployments.

B. Preliminary Stair Analysis

1) *Methods:* Data collected from the proposed wearable system in this work was used to conduct a preliminary analysis on stair negotiation. Since the focus on this work is to present the wearable system itself rather than a detailed explanation on the stair analysis algorithm, we only briefly introduce the methods for the preliminary analysis as followed.

Stair climbs were detected from the wearable barometric pressure signal after smoothing with a 1 s moving average filter. A symmetric two-sided cumulative sum (CUSUM) change-point detector was used [26]: an onset accumulator integrated the directional pressure rate until a confirmation threshold was exceeded, and a complementary flatness accumulator terminated the event. Acceptance criteria were defined independently of staircase geometry using a minimum pressure excursion derived from the minimum expected height change (1.4 m), a minimum climb rate derived from the minimum expected vertical speed (0.05 m/s), and a permissive duration gate (2.5 s). The method therefore requires no prior knowledge of stair number, height, or dimensions. Pressure signals were averaged across body-mounted sensors, and detected events were matched to manually labelled stair flights to compute recall and precision.

For each detected stair climb, steps were estimated from the acceleration magnitude of each sensor using phase accumulation in the time and frequency domain. A complex Morlet continuous wavelet transform (CWT) was computed over a location specific frequency range, and the dominant frequency ridge was extracted and integrated over the climb window to obtain the raw number of acceleration cycles. The raw cycle count was converted to a stair count using a gait multiplier defined by sensor location and walking pattern. For normal alternating gait, the ankle count was doubled because each foot contacts only half of the stairs, while wrist and lower back signals correspond directly to the number of stairs. For BES, the ankle multiplier was one, and wrist and lower back multipliers were one half. The frequency range was chosen per sensor so that the ridge followed the fundamental oscillation rather than a harmonic. Stair estimates from all sensors were averaged, yielding a count that accommodates cadence variation during stair walking. Estimates were compared with the known staircase length of 10 steps.

Handrail use was inferred from the dominant oscillation frequency of the wrist acceleration signal during stair ascent. This frequency was obtained from the wrist CWT ridge and summarised as the median value over each detected stair flight. The rationale is mechanical: during unaided ascent, the arm swings freely at the arm or stride cadence, whereas gripping the handrail constrains and damps wrist motion, which is expected to change the dominant wrist oscillation frequency. Because the number of stair flights was limited, the sample sizes were unequal between conditions, and the frequency distributions

were not assumed to be normal, normal and handrail-assisted ascents were compared using a two sided Mann Whitney U test. Separability was then quantified from the same statistic as the area under the receiver operating characteristic curve (AUC), defined as $AUC = U/(n_1n_2)$, where U is the Mann-Whitney statistic for normal ascents and n_1, n_2 are the number of normal and handrail-assisted flights. This value represents the probability that a randomly selected normal ascent has a higher wrist oscillation frequency than a randomly selected handrail-assisted ascent, where $AUC = 0.5$ indicates chance level separation and $AUC = 1$ indicates perfect separation.

2) *Results:* The results of the preliminary analysis is presented in Figure 4. The barometric CUSUM detector recovered all manually labelled stair flights, with 119 out of 119 flights detected, corresponding to 100 % recall, and achieved 88 % precision with 16 spurious events across six participants (data from one participant was excluded due to IMU packet loss). These results confirm that the proposed wearable system with a change point detector and geometry-free thresholds can identify stair use reliably without prior knowledge of staircase dimensions. The few false positives were associated with other rapid altitude changes, such as sit to stand transitions and during-session occasional jump movements.

Step counting based on the wavelet ridge tracked the ten step staircase with a mean absolute error (MAE) of 1.7 steps. This corresponds to approximately 17 % of the staircase length. A mild systematic underestimation was observed, consistent with occasional missed cycles when packets were lost or limb motion was weak. This level of accuracy may be sufficient for coarse mobility indicators, such as climbs per day or steps per climb, but a more detailed threshold optimisation and sensitivity study are required before this can be applied for detailed gait analysis or treated as a meaningful biomarker.

Finally, handrail use was clearly separated from unaided ascent using a single wrist feature. Gripping the handrail reduced the median arm swing frequency from 1.72 Hz to 1.17 Hz. The difference was statistically significant according to a two sided Mann Whitney U test, with $p \approx 2 \times 10^{-5}$, and the corresponding AUC was 0.92. This indicates 92 % rank separability between normal and handrail-assisted ascents. The result suggests that a wrist based feature can provide a compact marker of compensatory reliance on support, although the stair flight samples are not fully independent and the finding should be confirmed in a larger cohort with participant level analysis.

V. CONCLUSION AND FUTURE WORK

As described above, we find that network performance, reliability and timing are suitable for the intended monitoring purpose, although delivery performance on one of our initial prototype sensors was adversely affected by a hardware deficiency. From preliminary analysis of the resulting data, we find that the system has the ability to reliably deliver IMU and pressure data at an appropriate sample rate for the analysis of stair negotiations, with a detection recall of 100 %, a precision of 88 %, a step count MAE of 1.7 and a 92 % separability between normal and handrail-assisted ascents. In

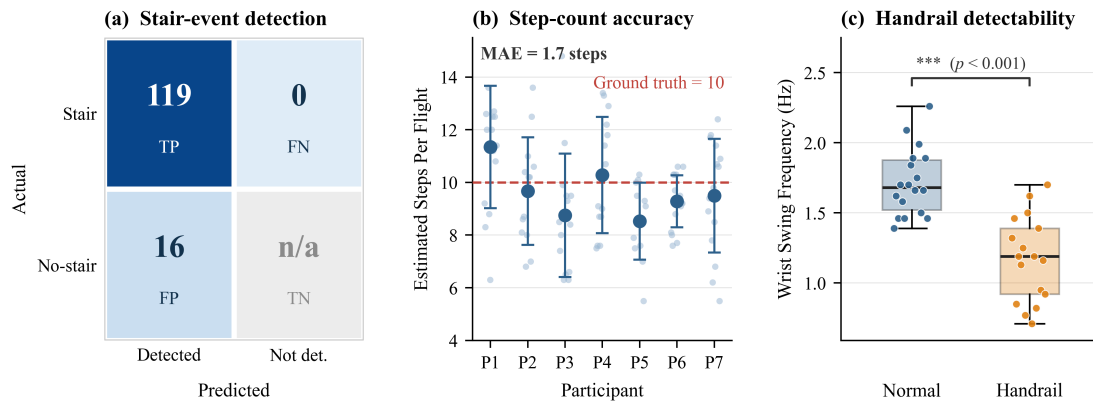


Figure 4. Summary of preliminary stair negotiation analysis on (a) stair event detection, (b) on stair step count accuracy and (c) handrail detectability.

our future work, we will assess the performance of this system in characterising stair climbing and descent rates and strategies used in participants with Parkinson's.

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