CuePD: An IoT approach for Enhancing Gait Rehabilitation in older adults through Personalised Music Cueing

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Abstract— Falls in people with Parkinson's disease (PwPD) underscore the need for precise sensing tools to robustly assess gait and deliver tailored rehabilitation. Using wearable inertial measurement units (IMUs) offers a practical alternative to assess gait and intervene in any location. This study develops a robust and innovative smartphone application/app that uses embedded IMU for real-time gait sensing to facilitate personalised cueing for targeted rehabilitation to reduce falls. Here, older adults had their *CuePD* based gait validated against a reference standard and were then exposed to different but personalised cueing modalities to target a 10.0% increase on cadence. *CuePD* increased cadence by 8.3% and showed robust agreement with the reference before and after cueing as evidenced by strong Pearson correlation coefficients (≥0.843) and intraclass correlation coefficients (≥0.845) across clinically relevant temporal gait characteristics (e.g., step time). Gait sensing via a smartphone is robust and *CuePD* indicates the feasibility of a scalable and personalised approach for targeted gait rehabilitation. Future research will extend to PwPD.

Index Terms— real-time gait assessment, personalised music cueing, Parkinson's disease, smartphone rehabilitation

I. INTRODUCTION

Neurological disorders are among the primary contributors to limited mobility and significantly heighten the risk of falls [1]. Any increased occurrence of falls can result in serious injuries which are often fatal, while also diminishing an individual's confidence in carrying out tasks of daily living [2]. That further escalates the risk of subsequent falls, creating a cycle of fear and vulnerability [3]. Accordingly, many people find it difficult to actively participate in the community, leading to a decline in their quality of life. [4].

Hypokinetic movement disorders, such as Parkinson’s Disease (PD), adversely impact mobility and increase fall risk through gait disturbances, with stride variability directly related to an increased fall risk [5]. Subjective assessment involves trained physical therapists visually assessing an individuals' gait, with experience identifying subtle disturbances [6]. Yet, subjective observation alone means unreliability [7] and lack of consistency within and across patients [8].

Advanced gait assessment using laboratory-based instrumented walkways provides objective insights via high resolution data. Yet, the significant expense, technical requirements, and confinement to a bespoke setting restrict their practicality and widespread adoption [9]. This emphasizes the need to adopt more pervasive and scalable approaches with gait sensing technology to readily retrain gait.

Scalable and more readily accessible gait related technologies could provide better mechanisms to leverage tailored (personalised) rehabilitation programs [10]. The latter are designed to address and rectify nuanced gait disturbances through focused and customized gait retraining [11]. Several methods of gait retraining have been explored, but typically it is sensory cueing that leads to substantial improvement when compared to other approaches e.g., treadmill or virtual reality training [12]. Among cueing modalities, auditory cueing is an effective and pragmatic intervention [13]. Auditory cueing typically employs a metronome's rhythmic beat to help a listener establish a consistent walking tempo, with clinical protocols using digital devices to administer the metronome beat. Yet, a metronomes monotony reduces long-term engagement and although music offers a more engaging alternative, its effectiveness is limited by a lack of personalization [14]. Therefore, the efficacy and validity of personalised music cueing should be further explored within a scalable and accessible context.

This study continues the development and sensing validation of *CuePD*, a smartphone app for future use in people with PD (PwPD), a real-time personalised cueing method for gait rehabilitation [15]. The main novelty and contribution of this letter is a robust inbuilt smartphone sensor-based gait (i) recognition for (ii) personalized rehabilitation. The purpose is to produce an open, scalable and contemporary tool via a single device.

II. RELATED WORK

This section underscores the clinical and technical foundation for this study. Specifically, how personalised auditory cueing through sonification via a single sensing device can offer more effective and tailored rehabilitation, where *CuePD* provides a single-device solution. To facilitate cost-effective, accessible and robust gait assessment anywhere, wearable inertial measurement units (IMU) is prevalent [16]. IMUs are highly effective in capturing gait characteristics that are comparable with those obtained from traditional technology (e.g., instrumented walkway). Bespoke wearable IMUs exist but they have similar barriers to use as lab-based technologies e.g., cost, technical requirements. Smartphones (with embedded IMUs) are suggested as a pragmatic and scalable alternative [17].

A. Smartphone: Inertial sensing

Gait assessment using IMUs involves the collection and analysis of data from accelerometers and/or gyroscopes, which can be performed in near real-time, crucial for rehabilitation techniques that incorporate biofeedback [18]. Smartphones generating those inertial sensor data necessitates direct interaction with the operating system (OS) via specifically designed application programming interfaces (APIs). In cross-platform development, frameworks like React-Native leverage APIs exist such as 'react-native-sensors' to streamline sensor data generation, enhancing workflow efficiency across multiple platforms and driving widespread adoption.

B. Gait: Data capture and algorithms

IMUs placed on the lower back (5th Lumbar Vertebrae, L5) have demonstrated robust effectiveness in conducting gait assessments when combined with a continuous wavelet transform (CWT)-based algorithm. Specifically, phases of the gait cycle can be accurately identified from the initial contact (IC) and final contact (FC) events arising within inertial data [19]. From those events, temporal gait characteristics such as step time can be calculated [20].

C. Gait Rehabilitation: Auditory cueing

Auditory cueing traditionally employs a metronome at a set beat(s) per minute (BPM), where an individual attempts to walk in time to each beat to reduce any gait disturbance(s). For example, use of a metronome as a cueing mechanism has shown improvements in gait for people with PD (PwPD) where gait velocity and step amplitude improved during different walking conditions [21]. Moreover, as music is recognized for its therapeutic effects it has been applied as a cueing mechanism to provide a more engaging alternative. Accordingly, music cueing has also improved gait in PwPD. Yet, the lack of personalization in music cueing can result in nearly half of PwPD experiencing no improvement or a decline in gait following treatment, emphasizing the importance of a more tailored approach [22].

D. Advancing auditory cueing: Sonification

Sonification conveys information or data via non-speech audio. Its use in gait retraining is recognised, but a notable application is the manipulation of music cues to match an individual's cadence i.e., adjusting music BPM to an individual’s steps per minute (SPM) using time-stretching algorithms [23]. A BPM +10% on an individual's natural cadence shows signs of reduced gait variability ($p < 0.03$), with lasting effects up to 15 minutes post-observation in PD [24]. Furthermore, the personalization of music cueing, tailored to an individual's cadence (1-20% increase), was conducted using inertial data from wearables on each foot and a smartphone app. That approach was deemed "*easy to use*" by 75% of the participants and contributed to a reduction in the fear of falling [25].

III. METHODS

A. Participant recruitment

Approval to conduct the study was granted by the Northumbria University Research Ethics Committee (Ref: 3231). Ten older adults were recruited (5F:5M, 62.3 ± 4.2 years, 78.6 ± 15.9kg, 168.0 ± 15.1cm) from the community in the North East of England. All participants provided written informed consent before testing.

B. Data capture: Smartphone and reference

Participants were asked to wear an Apple iPhone XS (177g, 143.6×70.9×7.7 mm) on L5 using a belt strap and holder, with the screen facing out and the lighting port downward, Fig. 1. The iPhone XS has a tri-axial accelerometer (BMI160, Bosch), capable of measuring acceleration forces up to ±8g, with an output data rate of 100 Hz, 16-bit resolution, and low power consumption of 950 µA in normal mode.

Gait characteristics from the smartphone were compared to a reference IMU (Opal: https://apdm.com/wearable-sensors/) worn on the talus joint of each foot. For each walking task, accelerometer data were recorded by the smartphone (100 Hz) and reference (128 Hz). Participants selected music (from pop, rock, R&B, and country genres) and wore wireless headphones for the protocol, which were disinfected after each use.

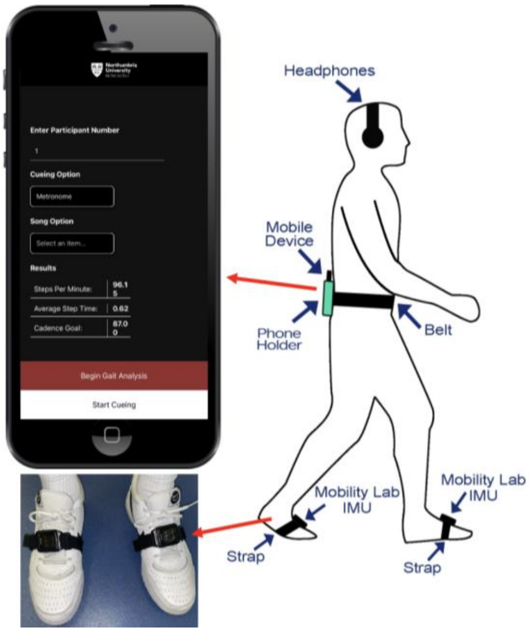

Fig. 1. Smartphone and reference attached to lower back and feet.

All walks were 1-min in duration in a continuous 25m loop, Table 1. Walk #1 was at the participant's usual pace to calculate a baseline cadence. Walks #2 to #4 were cued. A washout period followed Walks #2 and #3, where participants counted backwards in their head from 30 to 0 in increments of 1 to disengage psychological responses evoked by each cueing modality and minimize any carryover effects [26].

Table 1. Walking protocol

Walk #	**Description**	***Washout after?***
1	25m flat surface loop at self-selected pace.	No
2	25m loop with metronome cueing set at +10% baseline cadence	Yes
3	25m loop with instrumental music cueing set at +10% baseline cadence	Yes
4	25m loop with vocal music cueing set at +10% baseline cadence	n/a

C. System architecture and operation

The app, built in React Native with JavaScript, uses react-native-sensors to capture accelerometer data. It includes a countdown for data recording and after each 1-minute session, it transmits data to a Python server on Azure through a RESTful API. That server uses Flask on Azure's virtual machine to process and store the data. To streamline *CuePD*, audio files for each cueing mechanism are stored as MP3 files and hosted on the Azure server. When the user initiates cueing, the server adjusts the tempo of the audio file using a time-stretching algorithm. That adjustment aligns the music's beats-per-minute (BPM) with the user's steps-per-minute (SPM) plus 10%. The tailored audio is then sent back to the app.

D. Gait characteristic and cueing mechanism

Acceleration data were serialized into JSON and transmitted via HTTPS POST to a Flask server on Azure for gait analysis. Raw inertial data were filtered (4^{th}-order Butterworth) and then processed via a Python framework to correct for accelerometer misalignment (offset) by subtracting mean acceleration values and by transforming to a horizontal-vertical coordinate system [30]. Then a CWT algorithm extracted ICs and FCs in the gait cycle [19] to calculate gait characteristics: step time (seconds/s), stride time (s), stance time (s), swing time (s), and cadence/SPM (average time intervals between successive IC events divided by 1-min/60s) [20]. Previously, the IC/FC algorithm [19] has been comprehensively validated in older adults [27], [28], [29].

Baseline cadence (Walk #1) underwent a +10% augmentation before input in the cueing mechanism. Gait characteristics from Walks #2 to #4 were quantified to validate the effectiveness of the cueing mechanism in altering gait dynamics (based on the +10% augmentation), Fig. 2. The cueing mechanism incorporated three cueing modalities: a metronome, a song selected by the participant but with vocals removed (instrumental), and the same song but with the vocals persevered (vocal). From the music choice, 6 participants opted for pop, 3 chose rock, and 1 selected country music.

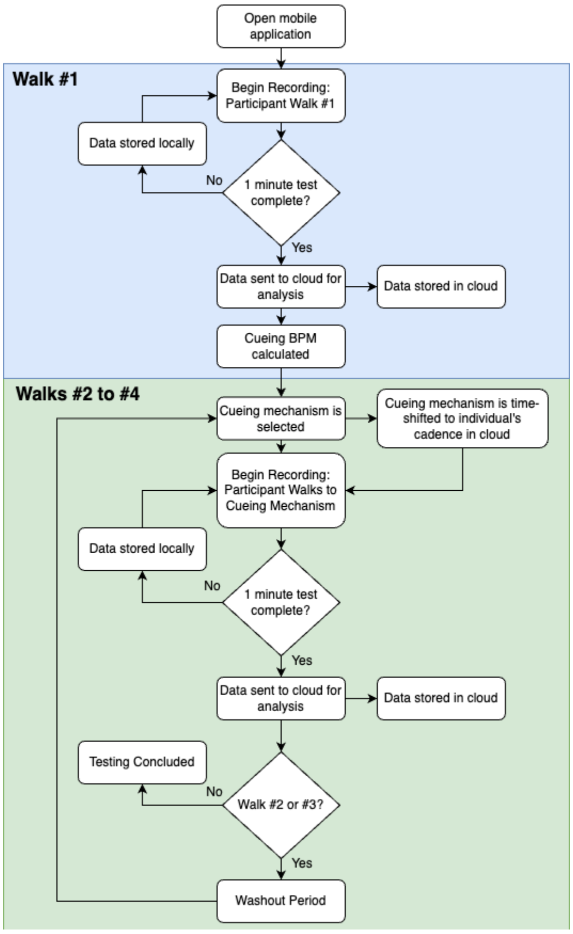

Fig. 2. Flowchart for system architecture and testing protocol.

E. Statistical Analysis

All gait characteristics (*CuePD* and reference) were compared via intra-class correlation coefficients ($ICC_{2,1}$) and Pearson's correlation coefficients (PCC). Within the 95% confidence interval of the $ICC_{2,1}$ estimate, <0.5 denotes poor agreement, 0.5-0.75 moderate, 0.75-0.9 good and 0.9-1.0 excellent [31]. PCC are categorized as zero (0), weak (±0.1 to ±0.3), moderate (±0.4 to ±0.6), strong (±0.7 to ±0.9), and perfect (+1 or -1) [32].

F. CuePD usability

Following walks, participants completed the system usability scale (SUS) which assessed perceptions of app use, complexity, and satisfaction [34]. SUS provides a score from 0 to 100, calculated by aggregating adjusted scores from 10 questions which involve subtracting 1 from odd-numbered question scores, while for even-numbered questions, subtracting its score from 5. This yields values between 0 and 4, which are summed and then multiplied by 2.5 to obtain the final SUS score, higher scores indicate better usability.

IV. RESULTS

A. Gait validation: No cue, walk #1

All $ICC_{2,1}$ values across all gait characteristics ranged from 0.889 to 0.981 i.e., good to excellent levels of agreement between *CuePD* and reference. Pearson coefficient values ranged from 0.924 to 0.992, indicating strong positive correlations, Table 2.

Table 2. Validation results

Cue	Characteristic	$ICC_{(2,1)}$	PCC	Mean Error
No Cueing	Step Time (s)	0.951	0.975	0.010
	Stride Time (s)	0.981	0.988	0.016
	Stance Time (s)	0.963	0.959	0.018
	Swing Time (s)	0.889	0.924	0.016
	Cadence (steps)	0.979	0.992	1.309
Metronome	Step Time (s)	0.997	0.998	0.003
	Stride Time (s)	0.995	0.993	0.006
	Stance Time (s)	0.946	0.943	0.019
	Swing Time (s)	0.845	0.843	0.017
	Cadence (steps)	0.992	0.991	0.935
Instrumented music	Step Time (s)	0.984	0.989	0.006
	Stride Time (s)	0.993	0.993	0.009
	Stance Time (s)	0.963	0.970	0.015
	Swing Time (s)	0.857	0.884	0.013
	Cadence (steps)	0.989	0.992	0.925
Vocal music	Step Time (s)	0.991	0.991	0.005
	Stride Time (s)	0.988	0.990	0.008
	Stance Time (s)	0.959	0.989	0.016

Cue	Characteristic	$ICC_{(2,1)}$	PCC	Mean Error
	Swing Time (s)	0.849	0.893	0.013
	Cadence (steps)	0.991	0.992	0.938

B. Gait validation: Personalised cueing, walks #2 to #4

All $ICC_{2,1}$ values (0.845 to 0.997) indicate strong to excellent levels of agreement between *CuePD* and reference. Similarly, there were strong positive correlations (PCC) with values ranging from 0.843 to 0.998, Table 2. We also assessed *CuePD*'s effectiveness in using personalised cues to increase cadence (+10% from baseline). Results show a mean increase across all modalities: 7.4% (metronome), 7.6% (instrumental), and 8.3% (vocal), Table 3.

Table 3. Cueing Increase

Cueing	Mean	Median	SD	Min	Max
Metronome	7.4%	7.9%	2.1%	3.3%	10.1%
Instrumental	7.6%	7.6%	2.1%	4.1%	11.1%
Vocal	8.3%	8.7%	1.5%	5.7%	10.1%

C. System Usability Scale

SUS results indicate a positive collective response yielding an overall score of 76, which indicates 'good' usability [34]. This reflects a consensus among participants regarding the system's ease-of-use and user-friendliness.

V. DISCUSSION

CuePD's novelty lies in combining real-time gait assessment and personalized (music) cueing rehabilitation into a single smartphone app, offering a scalable, single-sensing approach. Here, this study examines *CuePD* validity and effectiveness to adjust gait (increase cadence) in older adults. Results show that *CuePD* is a valid and effective tool for near real-time gait assessment and personalised auditory cueing (via sonification) in older adults. *CuePD* is suggested as a more efficient and streamlined (i.e., single-sensing device) approach to improve upon a previous approach [35] that used numerous technologies i.e., a smartphone app with IMUs on the feet. By eliminating the need for multiple devices via different attachment locations, *CuePD* simplifies the approach to aid cost-effectiveness, user-friendliness, and accessibility. Here, we attain comparable effectiveness in personalised music cueing and gait assessment through a single device which signifies a significant advancement towards pragmatic and scalable use.

Validity of *CuePD* derived gait characteristics during all walks were established to a reference standard with excellent ICCs that were comparable to validation findings in younger adults [15]. This suggests that *CuePD* (and associated approaches i.e., use of smartphones as sensing modalities) could be useful across the life course for gait assessment [21]. However, validity in clinical cohorts is yet to be established (see limitations and future work).

Participants highlighted music as the most engaging method of cueing. Like previous work [14], participants reported that aligning their steps to the personalized music (here, both instrumental and vocal) was more intuitive compared to personalized metronome alone. One participant remarked that "*vocal requires less thought*", corroborated generally by the data with a mean cadence increase of 8.32% (vocal, Table 3) which closely aligned with the target of 10%. Furthermore, with a mean positive usability score of 76, participants found *CuePD* user-friendly and simple to use, which suggests strong acceptance and satisfaction for longer deployment.

A. Limitations and future work

No adults with physical impairments were included. Current work is recruiting PwPD to explore the clinical impact of *CuePD* use on Parkinson's gait, including fallers vs. non-fallers.

VI. CONCLUSION

CuePD is a valid gait sensing tool and effective for personalised cueing via sonification in older adults. Moreover, *CuePD* has good usability and most effectively modified cadence via personlaised vocal music. *CuePD* may be a viable and scalable gait retraining tool to offer a practical, single-device approach for personalised at-home gait assessment and rehabilitation to reduce fall risk.

ACKNOWLEDGEMENTS

This research is co-funded by a grant from the National Institute of Health Research (NIHR) Applied Research Collaboration (ARC) North East and North Cumbria (NENC). This research is also co-funded by the Faculty of Environment and Engineering at Northumbria University. The authors would also like to thank all participants who took their time to complete this study.

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