Human-in-the-loop Cueing Strategy for Gait Rehabilitation

Tina LY Wu¹, Anna Murphy², Chao Chen³, and Dana Kulić⁴

Abstract—External feedback in the form of visual, auditory and tactile cues has been used to assist patients to overcome mobility challenges. However, these cues can become less effective over time. There is limited research on adapting cues to account for inter and intra-personal variations in cue responsiveness. We propose a cue-provision framework that consists of a gait performance monitoring algorithm and an adaptive cueing strategy to improve gait performance. The proposed approach learns a model of the person’s response to cues using Gaussian Process regression. The model is then used within an online optimization algorithm to generate cues to improve gait performance. We conduct a study with healthy participants to evaluate the ability of the adaptive cueing strategy to influence human gait, and compare its effectiveness to two other cueing approaches: the standard fixed cue approach and a proportional cue approach. The results show that adaptive cueing is more effective in changing the person’s gait state once the response model is learned compared to the other methods.

I. INTRODUCTION

Assistive robots have been applied in gait rehabilitation physiotherapy for Parkinson’s Disease (PD), stroke, spinal cord injury, and others [1], [2]. The robots can appear in the form of exoskeletons (e.g. LokoMat and ReWalk [3]), capable of monitoring the patient’s joint motion in real time and providing assistive torques to guide the movement of the patient [1]. The high cost of exoskeletons, ranging from $35,000 USD to $400,000 USD [4], can be prohibitive for patients to use in their daily lives. For patients who do not require load-bearing assistance, an alternative to exoskeletons are wearable devices that can provide simple feedback such as visual, auditory, and tactile cues to help patients both during therapy and in their daily activities [1], [5]. Visual cues such as laser projections provide spatial information on where to step next, whereas auditory and tactile cues provide temporal information on when to step by playing metronome beats or vibrations [5].

Existing research on cues focuses on providing visual cues at a fixed distance or auditory/tactile cues at a fixed pace calibrated to each patient [6], [7], [8], [9]. These cue provision paradigms have several limitations that are particularly problematic for long-term use and diseases with progressive symptoms such as PD. For instance, the cueing mechanisms are often used in conjunction with medications for PD treatment, and the same patient can respond differently to the cues depending on the medication state [5]. In addition, long-term use of the cues can result in habituation, where the cues become less salient and lose their effectiveness. Patients might also develop cue-dependency, where they become reliant on cues even without gait abnormalities [10]. Current cueing mechanisms do not address symptom fluctuation, habituation or cue-dependency and thus, there is a need to develop a cue adaptation strategy to address issues with static cues.

We propose an adaptive cue-provision framework that can simultaneously monitor the person’s gait performance and provide personalized cues to change the person’s gait to a desired state. Personalized cues are provided by continuously learning a model of the individual’s response to the provided cues, and utilizing the model to optimise cue selection. The performance of the adaptive cueing strategy is compared to two alternative cueing approaches, the fixed cue and the proportional cue. The fixed approach implements the typical cueing approach in the literature. The proportional approach is a semi-adaptive strategy that generates cues based on individual user performance, but using a fixed control strategy. The results show that adaptive cueing outperforms the other two cueing methods in changing the participant’s gait once the personalized response model has been learned.

II. RELATED WORK

An overview of the current literature with respect to the two primary features in an assistive feedback system, patient monitoring and providing personalized feedback, are presented in this section.

A. Monitoring Gait Parameters

Gait performance can be quantified using parameters such as stride length, cadence, velocity, and double support time [11]. Methods for calculating gait parameters for cue-provision can be categorized into approaches that are used in clinical or everyday settings.

In a clinical setting, the gait velocity and stride length can be manually measured using standard clinical tests. In [12], the patient’s velocity is measured by timing a 10-meter walk test and the stride length is calculated by counting the number of steps taken in 20 meters. There are also technologies to help automate the process. For instance, the VICON (VICON Motion Systems, Oxford, U.K.) and the GAITRite system (CIR Systems Inc, New Jersey, U.S.A.) (e.g. [11], [13]) are two commercially available gait performance measuring devices. However, these systems are typically employed to evaluate the effectiveness of cues, rather than being used as a feedback signal to the cueing system.

¹Tina and ⁴Dana are with the Department of Electrical and Computer Engineering, Monash University, Australia
²Anna is with the Clinical Research Centre for Movement Disorders and Gait, Monash Health, Australia
³Chao is with the Department of Mechanical and Aerospace Engineering, Monash University, Australia
Corresponding author: lee.wu@monash.edu
Sensors that are portable, unintrusive, and easy to set up, such as inertial measurement units (IMU) or encoders, have been embedded onto wearable devices to measure gait metrics outside of the clinical setting and provide information for the cueing system to adjust the cues. For instance, in [13], the authors developed a laser projection system that can be mounted onto a walking frame. The system adjusts the location of the visual cues based on the movement of the person measured through encoders embedded on the walking aid to ensure that the projection is always a fixed distance ahead of the person. Stride length has also been measured through sensor fusion algorithms using the gyroscope and accelerometer signals from IMUs to adjust for the location of the visual cues [14].

B. Providing Personalized Assistance

Personalization of the cues usually comes in the form of changing cue modality and location, and form factors. For instance, visual cue personalization can include adjusting for the distance of the projected line proportional to the user’s height, or location of the device on the user (e.g. foot-straped wearables like Path Finder LaserShoes (Walk with Path, Essex, England), walking aid based projection system like U-Step Walker (U-Step Mobility Products, Inc; Illinois, USA), or Augmented-reality glasses [14]).

Auditory and tactile cue adjustments share common tuning parameters, such as the duration of the cues (i.e. continuous or on-demand), frequency of the cues (i.e. paces ranging from a set speed to patient-specific speed), and timing of the cues (e.g. reactive or proactive, synchronization to the gait cycle events). There are characteristics unique to auditory cues such as providing music melody, human voice, or metronome beats [15]. The parameter unique to tactile cues is the amplitude and the pattern of the cue. Various forms of vibration have been tested (e.g. constant [16], or variable [17]) and can be provided via electrical stimulation [18] or vibration motor [16]. The effect of the tactile cue location has also been examined [5], [19], [18].

Online feedback adaption, including human-in-the-loop (HIL) optimization, has been investigated for robotic exoskeletons. In the HIL framework, real-time adjustment of the assistance is implemented based on the current performance of the user. Specifically, the HIL framework has been applied in optimizing the assistive force provided by exoskeletons to reduce metabolic cost during walking [20], [21], [22]. A fundamental requirement for HIL is building a model that relates the input assistive force to the output performance metrics. Previous studies have used a set of pre-defined assistive forces to uniformly explore the parameter space for the model [21]. Others have also investigated more sample-efficient methods without the initial parameter exploration by using gradient descent [20], [22] or Bayesian optimization [20]. To the authors’ knowledge, there is currently no research that examines cue adaptation beyond the one-time adjustment to calibrate the cue for the patient’s height, preferred cadence, or preferred location.

III. PROPOSED APPROACH

We propose an adaptive cue-provision framework, shown in Figure 1, that can continuously monitor the person’s gait performance and periodically adjust the assistance based on the person’s response to the feedback.

![Diagram](image)

Fig. 1. Block diagram of the proposed system. A feedback loop consists of the human, gait measurement, and cue provision. A model of the human gait is estimated online and provides metrics to evaluate gait performance. The Gaussian process regression model establishes a relationship between the provided cues and the measured changes in performance. Finally, the optimization block utilizes the Gaussian process model to provide personalized cues.

A. Online Gait Parameter Estimation

The canonical dynamical system (CDS) proposed in [23], which represents periodic signals using Fourier series, has been previously applied in online learning and modelling of an individual’s gait [24] and is used in this study. The gait is captured by a single inertial measurement unit (IMU) fixed above the individual’s knee of the dominant leg. The sensor is oriented such that the y-axis aligns with the normal of the sagittal plane. Once the gait model is learned, the associated model coefficients allows metrics to be derived for continuous monitoring. The CDS is defined as:

\[
\dot{y}_t = \sum_{m=0}^{M} \hat{\alpha}_{m,t} \sin(m\hat{\phi}_t) + \hat{\beta}_{m,t} \cos(m\hat{\phi}_t)
\]

where \(\hat{y}_t\) is the estimated signal, \(t\) is the current timestep, \(M\) is the total number of harmonics, \(\hat{\alpha}_{m,t}\) and \(\hat{\beta}_{m,t}\) are the Fourier series coefficients associated with the \(m^{th}\) harmonic, and \(\hat{\phi}_t\) is the phase of the signal. The coefficients are updated iteratively through the equations below:

\[
e_t = y_t - \hat{y}_t
\]

\[
\hat{\phi}_{t+1} = \text{mod}(\hat{\phi}_t + T(\hat{\omega}_t - \mu e_t \sin(\hat{\phi}_t)), 2\pi)
\]

\[
\hat{\omega}_{t+1} = |\hat{\omega}_t - T\mu e_t \sin(\hat{\phi}_t)|
\]

\[
\hat{\alpha}_{m,t+1} = \hat{\alpha}_{m,t} + T\eta e_t \cos(m\hat{\phi}_t)
\]

\[
\hat{\beta}_{m,t+1} = \hat{\beta}_{m,t} + T\eta e_t \sin(m\hat{\phi}_t)
\]

where \(y\) is the input signal to be learned (i.e. the gyroscope signal in the y-axis), \(\hat{\omega}\) is the estimated frequency, \(T\) is the sampling period in seconds, and \(\mu\) and \(\eta\) are the learning rates associated with the estimated frequency and Fourier series coefficients, respectively. \(\hat{\omega}\) is used as the primary gait
performance metric to represent the participant’s estimated cadence in the experiment described in Section IV. However, CDS provides information on the phase of the signal ($\hat{\omega}_t$), which allows for optimizing for the timing of the cue in the gait cycle in the future.

B. Learning of the Cue Response Model

In order to provide personalized assistance that accounts for the individual’s response to the feedback, a solution is formulated based on the HIL framework. The approach is similar to the Bayesian approach in [20], except there is no initial exploration with a pre-defined set of parameters. A Gaussian process (GP) is used to model the person’s response to a given auditory cue while walking at a given cadence. Specifically,

\[
\hat{\omega}_t = \hat{\omega}_t \\
Y = f(X) + H\beta, \\
\text{where } f(X) \sim GP(m(X), k(X, X')), \\
Y = \hat{\omega}_k, X = (\hat{\omega}_{k-1}, c_{k-1})
\]

where \(\hat{\omega}_t\) is the person’s estimated cadence at time \(t\) given by the CDS model; the index, \(k\), increments every four strides; when \(k\) is incremented at time \(t\), \(\hat{\omega}_t\) at that instance is directly written to \(\hat{\omega}_t\) as shown in Eq \(2\). \(c_k\) denotes the auditory cue frequency provided at increment \(k\) and is zero when no cue is provided. Both \(\hat{\omega}\) and \(c\) are in Hertz (Hz). The GP prior, \(f(X)\), is computed over the available data up to index \(k\), where \(Y\) is a list of the cadences, and \(X\) is a list of the preceding cadences and cue frequencies. New data gets appended to \(X\) and \(Y\) with each \(k\). \(m(X)\) is the mean function and \(k(X, X')\) is the square exponential kernel of the GP. An explicit, constant basis function, \(H\), is specified, where \(H\) is a k-by-one vector of ones and \(\beta\) is a scalar basis coefficient estimated from the data.

C. Cue Provision and Optimization

During the GP update, we also check whether the participant’s current cadence is within a threshold of the target cadence (\(u_{\text{target}}\)). If \(|\hat{\omega}_t - u_{\text{target}}| > \text{threshold}\), the expected value of the predictive posterior distribution is computed using the GP model given the current cadence and the available range of cue frequencies (±35% of the baseline cadence, \(\omega_{\text{baseline}}\)) to minimize the difference between the mean and the target cadence, as follows:

\[
\hat{\omega}_{k+1} = k((\hat{\omega}_k, c_k), X)(k(X, X) + \sigma^2 I_n)^{-1}(Y - H\beta)
\]

\[
J(\hat{\omega}_k, c_k) = (\omega_{\text{target}} - \hat{\omega}_{k+1})^2 \\
c_k = \arg\min_{c_k} J(\hat{\omega}_k, c_k), \text{ subject to} \\
\omega_{\text{baseline}} \times 0.65 \leq c_k \leq \omega_{\text{baseline}} \times 1.35
\]

where \(\hat{\omega}_{k+1}\) is the next cadence estimated from the GP model, \(I_n\) is a square identity matrix. The minimization algorithm is initialized with a randomly generated number. This random initialization is used for response space exploration; when a random starting point far away from the kernel is selected, the optimizer will exit immediately as the size of the gradient is less than the optimality tolerance. The random selection behaviour will stop once the gradient can be computed. Based on this property, the model can be interpreted as having two phases: the exploration (exp) phase (i.e. random sampling) versus the converged (cvg) phase (i.e. when there is a valid gradient). The two phases are discussed in Section VI.

The personalized cue provision algorithm described above is summarized in Figure 2. The algorithm is implemented in MATLAB, using the GP models (Statistics and Machine Learning Toolbox) and nonlinear least-squares optimization using trust region methods (Optimization Toolbox) [25].

IV. Experiments

We examined the effect of different auditory cue-provision strategies on cadence in the experiment, as auditory cues have been shown to have a strong influence on cadence [5].

A. Participants

A convenience sample of 25 participants (5 female and 20 male; age 26.08 ± 3.58 years; height 174.52 ± 8.65 cm; mass 70.88 ± 12.84 kg; mean ± standard deviation) enrolled in the study. All participants provided consent prior to the start of the experiment. The study (Project ID 22556) was approved by the Monash University Human Research Ethics Committee.

B. Materials

The motion data was recorded using a single IMU sensor with the WaveTrack Inertial System (Cometa Systems, Milan, IT). The data was sampled at 285 Hz and streamed wirelessly into a custom program in C#. The C# program ran on a laptop (windows 10, i7 core with no GPU), which controlled the timing of the auditory cues played from the computer and interfaced with MATLAB. The coefficients of
the gait parameter estimation algorithm, CDS, were initialized as the following: \( M = 7, \mu = 0.1, \eta = 1, \phi_0 = 0, \omega_0 = 2\pi \cdot \frac{2}{5}, \alpha_{m,0} = 0 \) for all \( \alpha_m \), and \( \beta_{m,0} = 0 \) for all \( \beta_m \).

C. Experimental Conditions

There were a total of 7 experimental conditions (1 control and 6 levels) in the study. In the control condition, the participants walked at their natural cadence with no cueing. The baseline cadence of each participant is measured during control and is used to calculate the two target cadences, which are \( \pm 20\% \) of the individual’s baseline cadence.

Following the control condition, each of the three cueing approaches was implemented for each target cadence: fixed, proportional, and adaptive. In the fixed cue approach, beats were provided directly at the target cadence described above, emulating the baseline cueing mechanisms in the literature where cues are provided at the target pace [8], [9]. In the proportional cue approach, the pace of the cue was proportional to the error between the participant’s current cadence and the target cadence. Specifically, \( c_k = \hat{\omega}_k + p_{\text{gain}} \times (\omega_{\text{des}} - \hat{\omega}_k) \), where \( \omega_{\text{des}} \) is the target cadence and \( p_{\text{gain}} \) is the proportional cue gain. The proportional approach serves as an intermediate comparison between the fixed and adaptive approach, as it accounts for the person’s current cadence but the error gain requires manual tuning and the gain remains the same throughout the experiment. The proportional cue gain was chosen to be 0.5, a value set empirically during pilot tests. Since the gain was small, the pace of the provided cues was close to the person’s current cadence. Finally, the adaptive approach was the algorithm that incorporated the participant’s individualized cue response model and optimization, described in Section III.

All three approaches provided cues only when the participant’s cadence was out of the acceptable boundary, set to \( \pm 1\% \) of the target cadence, as described in Figure 2. Eight metronome beats were provided if the acceptable condition was not met, one for each step. The number of beats was selected empirically as observed in the pilot study, where participants were able to change their gait within eight beats and the CDS model was able to converge to the new pace. Each experimental condition took 7 minutes to complete. The duration was as an extension of the Six-Minute-Walk clinical test. During the 7-minute experiment, cues were provided based on the acceptable criterion in the first 6 minutes, and no cue was provided in the last minute. The period of silence is used to evaluate the participant’s ability to maintain the target cadence in the absence of the beats.

D. Experimental Protocol

The participant watched an introduction video and placed the IMU sensor above the knee of the dominant leg during preparation. A short training session (\(<1\) minute) was provided to allow the participant to become familiar with the act of syncing one’s gait to the metronome beats, where a metronome beat at 1.3 Hz was played continuously for the participant to follow. After training, the participant completed the control condition where they walked in a big circle for 7 minutes without cues. They were told to walk naturally and forget about the practice metronome beats. The participant completed a demographic survey and proceeded to the experimental conditions. The order of the conditions was randomly generated for each participant. Participants were reminded to follow the beats provided. The participant repeated the cycle of the 7-minute walk followed by completing a NASA Task Load Index (TLX) survey 6 times. TLX is used to evaluate the participant’s cognitive workload in each experimental condition. Finally, the experiment was concluded after a debriefing session.

E. Analysis

The convergence of the GP was first assessed to validate its ability to model the person’s response to cues. The relationship between the experimental conditions and the resultant gait changes was then analyzed using linear mixed-effect models (LME) in R [26]. Square root transformation was applied to all data except the task load index score for the following analysis. The transformation helped with the normality and homoscedasticity assumptions during visual inspection of the residual plots. In general, the model satisfies these assumptions but contains outliers towards the tails. Data shown in the box plots in Section V are the un-transformed data for an easier interpretation. The fixed effects of the LME model are the different cue-providing approaches and the random effects are the intercepts for the individual participants. P-values were calculated using the likelihood ratio tests between the model without the fixed effect and the model with the fixed and random effects.

The performance of the cueing approaches (proportional and adaptive) were benchmarked against the baseline fixed cue approach. The analysis was grouped into the speeding up (UP) and slowing down (DOWN) conditions. For a more detailed analysis of the adaptive cue method, analysis was conducted with respect to the two phases of the GP model: the initial exploration (exp) during the first 70 seconds of the experiment and converged (cvg) model for the remaining time in the experiment. 70 seconds was chosen as it is the upper bound for the exploration phase seen in the data.

V. RESULTS

Adaptive Framework: Response Model Convergence

The GP modelling error and convergence, averaged over all participants and UP/DOWN conditions, are shown in Figure 3. Initially, the model has high variance and a high prediction error during exploration. The variance quickly drops off within 5 iterations as the algorithm learns the response model. However, the error variance does not decrease further until later in the experiment due to the fact that similar cues are often provided after the initial exploration. The result shows that GP is able to capture the participant’s behaviour around the target cadence.

Sample Experimental Data

A sample dataset from a participant is shown in Figure 4. The following metrics were used to quantify the performance of the cueing approaches:
**Target mean absolute error (MAE)** The target MAE is calculated as the mean absolute error between the participant’s estimated cadence and the target cadence. A low target MAE means the participant is able to change their original cadence to match the new target cadence. The LME model for UP shows that the effect of cueing method is significant (likelihood-ratio test statistic $\lambda_{LR} = 25.8837$, $p << 0.05$, standard deviation of the random effect (StdDev R.N.) = 0.0164). On average, the proportional approach has a higher target MAE compared to the fixed approach (Value = 0.0159, 95% Confidence Interval (CI) = [-0.0147, 0.0338], Standard Error (SE) = 0.016). The adaptive approach during exploration also has a higher target MAE than the fixed approach (Value = 0.0671, CI = [0.0266, 0.0756], SE = 0.0162). The adaptive approach when converged has a lower target MAE than the fixed approach (Value = -0.0216, CI = [-0.038, 0.0137], SE = 0.017).

For the DOWN conditions, the effect of the cueing method is also significant ($\lambda_{LR} = 56.3132$, $p << 0.05$, StdDev R.N. = 0.0276). The target MAE is higher in the proportional approach than the fixed approach (Value = 0.0383, CI = [0.0135, 0.0631], SE = 0.0127) and it is also higher for the adaptive approach during exploration compared to the fixed approach (Value = 0.0975, CI = [0.0724, 0.1227], SE = 0.0129). The adaptive approach once converged has a lower target MAE compared to the fixed approach (Value = -0.0076, CI = [-0.0338, 0.0185], SE = 0.0134). The results are shown in Figure 5.

**Intermediate MAE and Decay Rate** Intermediate MAE and decay rate indicate how well the participant is able to maintain the target cadence in the absence of the cue. Intermediate MAE measures the mean absolute error between the participant’s current cadence and the target cadence in the periods of silence during the first 6 minutes of the experiment. Decay rate is the rate at which the participant returns to a new steady state cadence after the final cue is provided. We calculate decay rate by fitting an exponential function to the cadence estimate. An example of the fitted decay rate data can be seen in the red lines in Figure 4. A low intermediate MAE and a low decay rate would indicate a better maintenance of the new cadence.

The LME model shows that for the UP conditions the effect of the cueing method is not significant for the intermediate MAE outcome ($\lambda_{LR} = 5.9734$, $p = 0.1129 > 0.05$, StdDev R.N. = 0.0115). For the DOWN conditions, the effect of the cueing approach is significant ($\lambda_{LR} = 35.9315$, $p << 0.05$).
Fig. 6. The intermediate MAE grouped by the UP (left) and DOWN (right) trials. The intermediate MAE is the highest for the proportional approach in both UP and DOWN trials. However, the effect of cueing conditions is only significant for the DOWN condition.

Fig. 7. The decay rate grouped by the UP (left) and DOWN (right) trials. The effect of the cueing condition is not significant for both UP and DOWN trials.

0.05, StdDev R.N. = 0.0235). The proportional approach has a higher intermediate MAE compared to the fixed approach (Value = 0.0512, CI = [0.0302, 0.0721], SE = 0.0107); the adaptive approach during exploration is also higher than the fixed approach (Value = 0.0434, CI = [0.0217, 0.0653], SE = 0.0111). The converged adaptive approach has an intermediate MAE lower than the fixed cue condition (Value = -0.007, CI = [-0.0285, 0.0144], SE = 0.0111). The results are shown in Figure 6.

Cueing approaches do not significantly affect the decay rate in the UP conditions ($\lambda_{LR} = 5.3566, p = 0.0687 > 0.05, \text{StdDev R.N.} = 0.1505$). Similarly, the cueing approaches also do not significantly affect the decay rate for the DOWN conditions ($\lambda_{LR} = 3.8148, p = 0.1485 > 0.05, \text{StdDev R.N.} = 0.0756$). The results are shown in Figure 7.

**Percent On**

In terms of minimizing the cue duration to reduce habituation, we quantified the cueing strategy performance using the percent on metric. Percent on represents the amount of time a strategy is providing beats expressed as a percentage of the first 6 minutes of the experiment.

For the UP conditions, the effect of the cueing method is significant ($\lambda_{LR} = 43.2037, p << 0.05, \text{StdDev R.N.} = 0.141$). The percent on time is higher for the proportional approach (Value = 0.1625, CI = [0.0679, 0.257], SE = 0.0484); the adaptive approach during exploration also has a higher percent on time than the fixed approach (Value = 0.2507, CI = [0.1562, 0.3453], SE = 0.0484). Once the adaptive approach has converged, the percent on time is lower than the fixed approach (Value = -0.0731, CI = [-0.1676, 0.0214], SE = 0.0484).

For the DOWN conditions, the effect of the cueing approach is also significant ($\lambda_{LR} = 44.7463, p << 0.05, \text{StdDev R.N.} = 0.1644$). The proportional approach playing cues more than the fixed approach (Value = 0.1517, CI = [0.0596, 0.2436], SE = 0.0471). The adaptive approach during exploration has the highest percent on time compared to the fixed approach (Value = 0.3164, CI = [0.2244, 0.4085], SE = 0.0471). The adaptive approach when converged is also higher than the fixed approach (Value = 0.014, CI = [-0.0779, 0.1061], SE = 0.0471).

**Participant Perception: NASA-Task Load Index (TLX)**

The sum of the raw TLX scores, which represents the participant’s cognitive workload in each condition, is analyzed.

For the UP conditions, the TLX score is not significantly influenced by the cueing approaches ($\lambda_{LR} = 1.2837, p = 0.5263 > 0.05, \text{StdDev R.N.} = 4.7480$). Similarly, the TLX
score is not significantly affected by the cueing approaches for the DOWN conditions ($\lambda_{LR} = 5.0589$, $p = 0.0797 > 0.05$, StdDev R.N. = 3.4140). The results are displayed in Figure 8.

VI. DISCUSSION

The target MAE in the adaptive approach is much higher in the initial exploration stage (exp) as the random number generator samples the response space. However, once the GP has converged (cvg), the adaptive approach has the lowest target MAE and the performance is consistent across the two target speeds. The converged adaptive approach reduces the target MAE by providing cues at a very different pace compared to the participant’s current state, prompting the participants to be more proactive, especially in the more cognitively demanding speeding up conditions as seen in Figure 9.

The proportional approach has the second highest target MAE and the highest intermediate MAE. This might be due to the fact that the proportional cue is not prompting the person to change much from the original cadence. In Figure 10, it can be seen that the difference between the cue and the current gait cadence is always the smallest for the proportional approach. The phenomenon is due to the choice of the controller gain, which is designed to provide gradual changes in the pace of the cue. While this gradual change allows for a lower cognitive workload (as seen in the TLX scores), the proportional approach is not as effective in changing the person’s cadence. The proportional approach is also used as an example of a one-size-fit-all cue-provision strategy, where the error gain is kept constant across all participants. While the proportional cue might have been more effective with a higher gain, the cueing method highlights the difficulty in manual gain selection.

In terms of the decay rate, the differences between the three cueing approaches are not significant. The results for both the decay rate and the intermediate MAE might be influenced by the participant’s memory (i.e. forgetting the pace of the cue over time) and their ability or willingness to adjust their cadence. In the post-study interviews, participants reflected that it was difficult to recall the pace of the cue in the long periods of silence. We also observed patterns in the experiment similar to the participant in Figure 4, where some participants immediately deviate from the target cadence when the cues are off, causing the drastic fluctuations and the on-off cueing pattern.

For the percent on time, the use of the adaptive method in the converged state performs similarly to the fixed approach. The percent on time should ideally be as low as possible to avoid habituation. However, the metric is not included in the optimization step as a term in the cost function and hence is not penalized. The effect of different cost terms will be investigated in the future.

Finally, the high TLX score for the adaptive approach, which is associated with the high cognitive workload, might be related to the initial exploration where the participant needs to follow a random set of beats. The pace of the cue is also consistently faster than the participant’s current state after the GP has converged as seen in Figure 10. A high TLX score suggests the adaptive approach might be more effective in addressing cue habituation as auditory cues correct gait by bringing attention to the walking task [5].

VII. CONCLUSIONS AND FUTURE WORK

We proposed an adaptive cueing framework that can simultaneously monitor gait performance of a person and adjust the auditory cues based on the person’s response. In the framework, we use a Gaussian process to model...
the relationship between the person’s gait as a function of the provided cues and past gait performance. Using the model, personalized assistance can be provided by finding the suitable cue parameters to improve gait performance. We investigated the effectiveness of the adaptive cueing strategy with healthy participants in a gait study, where we aimed to change the participant’s cadence with the cues. We compared the adaptive cue method to the fixed and the proportional methods. The results show that the proportional cues perform the worst among the three cueing approaches, highlighting the need for individualization and adaptation. The adaptive strategy outperforms the fixed strategy when the GP model has converged.

In the next stage of the study, the adaptive framework will be extended to consider additional objectives within the cost function, with the goal of providing multi-modal cues that are effective and easy to follow. With the single-session study, it is also difficult to examine the long-term effectiveness of the framework to address habituation. We plan on recruiting patients and extending the duration of the study to further investigate the framework.

REFERENCES
[1] L. Lünenburger, G. Colombo, and R. Riener, “Biofeedback for robotic gait rehabilitation,” Journal of neuroengineering and rehabilitation, vol. 4, no. 1, pp. 1–11, 2007.
[2] M. H. Thaut and M. Abiru, “Rhythmic auditory stimulation in rehabilitation of movement disorders: a review of current research,” Music perception, vol. 27, no. 4, pp. 263–269, 2010.
[3] D. R. Louie and J. J. Eng, “Powered robotic exoskeletons in post-stroke rehabilitation of gait: a scoping review,” Journal of neuroengineering and rehabilitation, vol. 13, no. 1, p. 53, 2016.
[4] A. Esquenazi, “Comment on “assessing effectiveness and costs in robot-mediated lower limbs rehabilitation: a meta-analysis and state of the art”,” Journal of Healthcare Engineering, vol. 2018, 2018.
[5] D. Sweeney, L. R. Quinlan, P. Browne, M. Richardson, P. Meskell, and G. O’Laighin, “A technological review of wearable cueing devices addressing freezing of gait in Parkinson’s disease,” Sensors, vol. 19, no. 6, p. 1277, 2019.
[6] A. Delval, P. Krystkowiak, M. Dellaux, J.-L. Blatt, P. Derambure, A. D’estée, and L. Defebvre, “Effect of external cueing on gait in huntington’s disease,” Movement disorders: official journal of the Movement Disorder Society, vol. 23, no. 10, pp. 1446–1452, 2008.
[7] R. S. Schaefer, “Auditory rhythm cueing in movement rehabilitation: findings and possible mechanisms,” Philosophical Transactions of the Royal Society B: Biological Sciences, vol. 369, no. 1658, p. 20130402, 2014.
[8] M. Bächlin, M. Plomin, D. Roggen, I. Maidan, J. M. Hausdorff, N. Giladi, and G. Tröster, “Wearable assistant for Parkinson’s disease patients with the freezing of gait symptom,” IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 2, pp. 436–446, 2010.
[9] V. Mikos, C. H. Heng, A. Tay, S. C. Yen, N. S. Y. Chia, K. M. L. Koh, D. M. L. Tan, and W. L. Au, “A Wearable, Patient-Adaptive Freezing of Gait Detection System for Biofeedback Cueing in Parkinson’s Disease,” IEEE Transactions on Biomedical Circuits and Systems, vol. 13, no. 3, pp. 503–515, 2019.
[10] P. Ginis, E. Nackaerts, A. Nieuwboer, and E. Heremans, “Cueing for people with parkinson’s disease with freezing of gait: a narrative review of the state-of-the-art and novel perspectives,” Annals of physical and rehabilitation medicine, vol. 61, no. 6, pp. 407–413, 2018.
[11] D. Conklyn, D. Stough, E. Novak, S. Paczak, K. Chemali, and F. Bethoux, “A home-based walking program using rhythmic auditory stimulation improves gait performance in patients with multiple sclerosis: a pilot study,” Neurorehabilitation and neural repair, vol. 24, no. 9, pp. 835–842, 2010.
[12] I. M. Park, D. W. Oh, S. Y. Kim, and J. D. Choi, “Clinical feasibility of integrating fast-tempo auditory stimulation with self-adopted walking training for improving walking function in post-stroke patients: a randomized, controlled pilot trial,” Journal of Physical Therapy Science, vol. 22, no. 3, pp. 295–300, 2010.
[13] H.-K. Wu, H.-R. Chen, W.-Y. Chen, C.-F. Lu, M.-W. Tsai, and C.-H. Yu, “A novel instrumented walker for individualized visual cue setting for gait training in patients with parkinson’s disease,” Assistive Technology, vol. 32, no. 4, pp. 203–213, 2020.
[14] A. Ahmed, H. Chung, H.-W. Lee, K. Kang, P.-W. Ko, N. S. Kim, and T. Park, “Smart gait-aid glasses for parkinson’s disease patients,” IEEE Transactions on Biomedical Engineering, vol. 64, no. 10, pp. 2394–2402, 2017.
[15] S. Ghai, I. Ghai, G. Schmitz, and A. O. Effenberg, “Effect of rhythmic auditory cueing on parkinsonian gait: A systematic review and meta-analysis,” Scientific Reports, vol. 8, no. 1, p. 506, dec 2018. [Online]. Available: [http://www.nature.com/articles/s41598-017-16232-5]
[16] C. Punin, B. Barzallo, M. Huerta, A. Berno, M. Bravo, and C. Llamiguano, “Wireless devices to restart walking during an episode of FOG on patients with Parkinson’s disease,” 2017 IEEE 2nd European Technical Chapters Meeting, ETMC 2017, vol. 2017-Janua, pp. 1–6, 2018.
[17] K. Yasuda, Y. Hayashi, A. Tawara, and H. Iwata, “Development of a vibratory cueing system using an implicit method to increase walking speed in patients with stroke: a proof-of-concept study,” ROBOMECH Journal, vol. 7, no. 1, pp. 1–8, 2020.
[18] L. Rosenthal, D. Sweeney, A.-L. Cunnington, L. R. Quinlan, and G. O’Laighin, “Sensory electrical stimulation cueing may reduce freezing of gait episodes in Parkinson’s disease,” Journal of Healthcare Engineering, vol. 2018, 2018.
[19] M. P. Pereira, T. L. Gobbi, and Q. J. Almeida, “Freezing of gait in parkinson’s disease: Evidence of sensory rather than attentional mechanisms through muscle vibration,” Parkinsonism & related disorders, vol. 29, pp. 78–82, 2016.
[20] M. Kim, Y. Ding, P. Malcolm, J. Speeckaert, C. J. Sivy, C. J. Walsh, and S. Kuindersma, “Human-in-the-loop bayesian optimization of wearable device parameters,” Plos one, vol. 12, no. 9, p. e0184054, 2017.
[21] J. Zhang, P. Fiers, K. A. Witte, R. W. Jackson, K. L. Poggensee, C. G. Atkeson, and S. H. Collins, “Human-in-the-loop optimization of exoskeleton assistance during walking,” Science, vol. 356, no. 6344, pp. 1280–1284, 2017.
[22] W. Felt, J. C. Selinger, J. M. Donelan, and C. D. Remy, “‘body-in-the-loop’: Optimizing device parameters using measures of instantaneous energetic cost,” Plos one, vol. 10, no. 8, p. e0135342, 2015.
[23] T. Petrić, A. Gams, A. J. Ipsen, and L. Žijač, “On-line frequency adaptation and movement imitation for rhythmic robotic tasks,” The International Journal of Robotics Research, vol. 30, no. 14, pp. 1775–1788, 2011.
[24] J. L. Waugh, E. Huang, J. E. Fraser, K. B. Beyer, A. Trinh, W. E. McIlroy, and D. Kulić, “Online learning of gait models from older adult data,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 733–742, 2019.
[25] M9.7.0.1261785 (R2019b), R Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2020. [Online]. Available: [https://www-R-project.org]