

GaitAssist: A Wearable Assistant for Gait Training and Rehabilitation in Parkinson’s Disease

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Abstract—Many patients with Parkinson’s disease suffer from short periods during which they cannot continue walking, the so-called freezing of gait. Patients can learn to use rhythmic auditory sounds as support during these episodes. We developed GaitAssist, a personalized wearable system for freezing of gait support, that enables training in unsupervised environments. GaitAssist detects freezing episodes from ankle-mounted motion sensors, which stream data via Bluetooth to an Android phone. In response, the system plays a rhythmic auditory sound that adapts to the patient’s regular gait speed. While GaitAssist can be used as a daily-life assistant, it also provides support for three types of training and rehabilitation exercises. The user can create personalized training sessions by adjusting the exercise and feedback parameters.

I. INTRODUCTION

Parkinson’s disease is a common neurodegenerative disease, for which there is no cure at the moment. Current treatment is mainly pharmacological and focuses on relief of motor symptoms. Many Parkinson’s disease patients experience the so-called Freezing of Gait (FoG), an episode during which their motor system is blocked and they can not continue walking [1]. These episodes last from few seconds up to one minute and they are a major cause for falling. Clinical studies showed that patients with FoG respond to gait-training exercises [2] and to Rhythmic Auditory Sounds (RAS) upon onset of FoG events [3], by resuming and improving their gait. Wearable assistive systems were built for this purpose [4], [5] but they are limited to be used only in laboratory-settings, with clinical supervision.

We present GaitAssist, a personalized wearable system for FoG support and gait training in unsupervised environments, such as the homes of the patients. GaitAssist can be used both as a daily-life assistant and as a support for FoG-rehabilitation exercises. Upon real-time FoG-detection, a rhythmic cue adapted to the patient’s gait speed is played back. GaitAssist is the result of incremental design and development carried out by interdisciplinary teams of engineers and clinicians that used feedback and data collected during extensive testing sessions with 18 Parkinson’s disease patients [6]. The system was used by 5 patients with FoG first in lab training sessions and then in their homes, as a support for the gait exercises, but also in-the-wild walking scenarios, e.g., walking in the park, as an assistive device. Their feedback is positive, a promising step towards the main purpose of the system – gait rehabilitation.

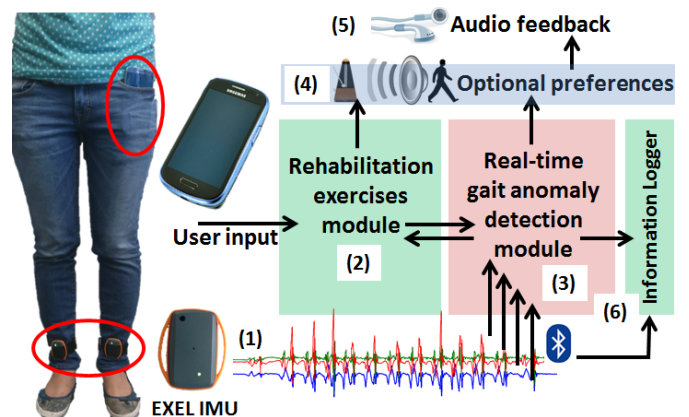


Fig. 1. The GaitAssist system with its components: (1) IMU sensors, (2) Rehabilitation exercises module, (3) FoG-detection module, (4) Preferences, (5) Feedback, and (6) Logging modules.

II. GAITASSIST SYSTEM

The two functionalities of the GaitAssist are: (1) *gait support* during daily-life activities to avoid or reduce FoG episodes, and (2) *training support* – as a personal assistant for the gait exercises. The core module of the GaitAssist system provides audio feedback to the user for a limited period of time, e.g., 20 s, at critical specific moments throughout walking when the gait is either *frozen* or resembles a gait pattern that may lead to FoG. The user of the system can choose whether to use the phone’s loudspeakers or earplugs to receive the audio feedback.

A. Hardware Components

To start the rhythmic cueing in real-time when a FoG occurs, the system continuously monitors and evaluates the gait of the user. Simultaneously, the system needs to be as unobtrusive and comfortable to wear as possible, and to not affect the motor performances of the user. After incremental design and evaluation sessions with engineers, clinicians and Parkinson’s disease patients, the system consists of at most two Inertial Measurement Units (IMU) attached on the ankles of the user, and a smartphone as a wearable computer as shown in Figure 1. The IMUs¹ sample accelerometer, gyroscope and

¹<http://www.cupid-project.eu/node/44>

magnetometer data. Acquired data is sent to the smartphone via Bluetooth in real-time. We use a Samsung S3 mini model, chosen because of its smaller shape (this model was best accepted by the patients), while providing enough computing capabilities to analyze the IMU data in real-time.

B. System Architecture and User Interface

The GaitAssist software consists of an Android application supporting the exercises and the assistive cueing, all based on the FoG-detection module that analyzes in real-time data received from the sensors. A simplified description of the architecture is presented in Figure 1 and includes the following modules:

(1) IMU sensors sample data and send it to the phone in real-time, via Bluetooth.

(2) In the *Rehabilitation exercise* module we support the following types of exercises: *gait initiation*, *turns*, and *response inhibition*, as designed by clinical specialists. These exercises are created to allow users to train their gait in difficult conditions. The module waits for the input of the user, to select the proper training exercise. Then it gives auditory cues for the start and the end of the exercise. It also supports the exercises with visual cues (e.g., random figures appearing periodically for the dual-tasking exercises, that trigger the movement of the user), and gives continuously rhythmic auditory stimulation during exercises, depending on the user's option.

(3) The *FoG-detection* module consists of two independent threads, each of them corresponding to an IMU. The system works with zero, one or two IMUs (one at each leg). When no IMU is attached the system is unable to perform FoG detection. In this case the system can still be used to provide support for the exercises, in the form of RAS, which may be useful for the user, as indicated by clinicians.

(4) In the *Preferences* module the user can set his preferences for the provided feedback. This includes different options for the metronome sounds, *beats per minute* settings for the metronome, and also the option to choose different FoG-detection models, which is also, related to the gait properties of the user.

(5) The *Feedback* module produces different types of rhythmic auditory cueing.

(6) The *Logging* module stores (a) the raw IMU readings, (b) the output of the FoG-detection algorithm, (c) statistics related to the number of FoG episodes and (d) their durations during the training sessions to internal memory. These data can be accessed later by the clinicians or sent to a telemedicine server. Thereby, the clinicians will be able to remotely observe the users' gait progress, and in response adapt the exercise program and difficulty settings.

The Android application consists of two separate main thread modules running in parallel: (a) the *Rehabilitation exercise* module and (b) the *FoG-detection* module. Based on the preferences set by the user, these two threads call the *Feedback* module. The GaitAssist user interface has four tabs: three tabs (*Gait Initiation*, *Turns*, and *Visual*) that support different types of training exercises. The options selected here are the input for the *Rehabilitation exercise* module. A fourth tab implements the *Preferences* module options.

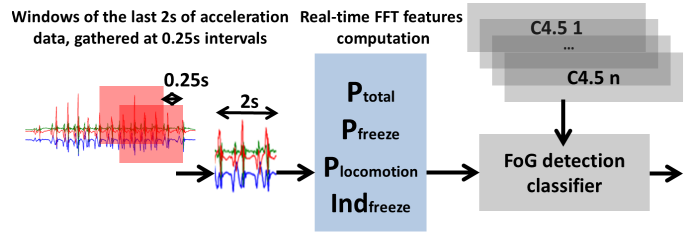


Fig. 2. The real-time FoG-detection chain from the GaitAssist system.

To ease the system setup and improve usability for the Parkinson's disease patients, the sensors automatically connect to the system once the GaitAssist application started. Once the *Start* button is pressed, all the widgets from the user interface are disabled, except the *Stop* button. This prevents the users from accidentally changing the exercise and setup parameters.

C. FoG-detection Algorithm

The real-time FoG-detection chain is presented in Figure 2. The IMUs sample data at $N_{sampling} = 32\text{Hz}$, chosen as a trade-off between IMU's battery power and the amount of data needed to observe changes in the gait properties. As the human movement range is between $0.5 - 16\text{Hz}$, a larger sampling rate will only waste precious battery power needed for a long term usage as an assistive device. 3D-Accelerometer data is segmented in overlapping windows of size $N_{window} = 2\text{s}$, with $N_{overlap} = 0.25\text{s}$. The most recent samples are stored in a circular buffer of size $N_{window} \times N_{sampling}$, continuously overwriting the oldest samples. The buffer is accessed at fixed intervals of length $N_{overlap}$, creating a window of data. The magnitudes over the all accelerometer-axes x , y , and z are computed in the window. From the vector of magnitudes the following FFT features are further analyzed: (1) Total power (P_{total}) between $0.5 - 8\text{Hz}$ bands, (2) Locomotion band power ($P_{locomotion}$) on $0.5 - 3\text{Hz}$, (3) Freezing band power (P_{freeze}) on $3 - 8\text{Hz}$ band, and (4) Freeze index (Ind_{freeze}) as described in [7]. The resulted feature vector is fed into a FoG-detection algorithm which decides in real-time whether the user is in FoG or not.

The FoG-detection algorithm consists of instances of supervised machine learning models, trained offline on labeled acceleration samples from 24 hours of collected data from 18 PD patients with FoG. Models were evaluated offline in a user-independent setting, meaning a general model was trained using data from all the patients. Overall the system achieves a FoG hit rate of 94.94% (169 out of 178 FoG episodes were detected) and a specificity 94%. The classification models were then integrated in the GaitAssist framework on the smartphone. We used C4.5 pruned trees trained with the FFT-based features, due to their good performance and the computational efficiency.

D. Performances and Power Consumption Analysis

We tested the system in a user study with 5 patients in a lab setting. The FoG real-time hit rate was 97% (99 out of 102), with a detection delay of 0.25 s on average. FoG events shorter than 0.25 s could not be detected. The false alarms were triggered typically in situations where the patients experienced related difficulties in walking.

The total time required for computing the FFT-features and making a decision in the FoG-algorithm is at most 1 ms, measured in real-time settings on the Android application running on the target platform. Furthermore the CPU usage during these operations does not exceed 50%. The computation latency is negligible compared to $N_{overlap}$ therefore we confirm that it does not influence the FoG detection latency.

In the assistive mode, the system can be used continuously up to around four hours. This limitation is given by the IMUs battery life. The currently used IMUs are under development and future versions will increase the IMU running time. However, at the end of these four hours, the phone battery's level is around 93%. This decreases slightly when using the system as a support for gait-training exercises, down to 85%. The increased consumption is caused by the continuous use of the UI (each exercise duration is about 5-6 minutes), and by the supplementary visual and audio cues.

III. DEMONSTRATION

During the demonstration, participants will be asked to attach the two IMU sensors on the ankle, independent of the sensor position and orientation. The sensors connect automatically to the phone as soon as the Android application is started. The participants will set their personal preferences: type of auditory cueing, cueing period of time, the cueing cadence, type of FoG-detection model, exercise time and other parameters as shown in Figure 3(a). A first scenario is to test the assistive functionality of GaitAssist – participants will perform movements as in a home- or in-the-wild- scenarios, e.g., walking with random turnings, passing narrow spaces, and will simulate different gait anomalies – falls, difficulties in walking with small steps, gait freezing simulations. The rhythmic auditory stimulation will turn on for a period of time. By following the rhythm imposed, users are able to resume and improve the gait properties.



(a) Preferences tab (b) Response inhibition tab

Fig. 3. GaitAssist app with the UIs for *Preferences* and *Response inhibition*.

A second demonstration scenario is performing a gait training exercise at the participant's choice, using the support of the GaitAssist. These exercises are specially designed by the clinicians to train the user's gait. For example, the *Response inhibition* exercise shown in Figure 3(b) is designed to train the gait of the user in a dual-tasking setup. The user is instructed

to start walking only when a specific green circle appears on the screen, and to stop walking when the system produces a special sound. This continues during the entire duration of the exercise. On the phone screen, random shapes and colors are displayed for a few seconds, forcing the user to concentrate while waiting for the green circle to appear. This concentration effort acts a FoG trigger and the patients have difficulties in starting walking. If a gait anomaly is detected during walking (difficulties in movement or FoG), the rhythmical cue starts, as in the assistive scenario.

A video example with a patient using the system as a gait assistant, at his home, is available at <https://vimeo.com/79472165>.

IV. CONCLUSION

In this demo we present GaitAssist, a personalized wearable system for gait training of patients with Parkinson's disease experiencing FOG, in unsupervised environments. The system is developed to be both a daily-life assistant, and a support for gait-rehabilitation exercises. GaitAssist was designed to be as unobtrusive as possible, and consists of a smartphone and two wearable IMUs attached to the ankles of the user. Its main functionality is to detect in real-time the gait anomalies of the users, such as FOG episodes. For this it uses machine learning models implemented on the smartphones and data received from the wearable IMUs. When a FOG episode is detected, the system initiates a rhythmic auditory cueing fit to the gait rhythm of the user, thus helping him to resume the walking. The core idea behind GaitAssist is that after a period of using the system as an assistive device or as a training device, the patients will experience an overall improvement of their gait properties.

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