Cueing of Parkinson's Disease Patients by Standard Smart Devices and Deep Learning Approach

Pavol Šatala[1], Peter Butka[1], Arsen Samaiev[1], Petra Levická[2]

[1] Department of Cybernetics and Artificial Intelligence, Faculty of Electrical Engineering and Informatics, Technical University of Košice, Letná 9, 04001 Košice, Slovakia; E-mails: pavol.satala@tuke.sk, peter.butka@tuke.sk, arsen.samaiev@student.tuke.sk

[2] Department of Neurology, Pavol Jozef Šafárik University in Košice, Faculty of Medicine, and Louis Pasteur University Hospital in Košice, Trieda SNP 1, 04011 Košice, Slovakia; E-mail: petra.levicka@student.upjs.sk

Abstract: Parkinson's disease is one of the most common neurological diseases. The patients suffer from different symptoms, e.g., tremor, bradykinesia, or walk gait disorders. One of the gait disorders which affects Parkinson's disease patients is freezing of gait, which shows as a sudden gait interruption without the ability to take the next step. It is hard to manage this symptom by medication. However, there are ways to address this symptom by applying different visual or vibration aids. This work presents a system for automatic detection and cue of freezing of gait events provided by ordinary smart devices. We used a deep learning approach to detect such events automatically. The test results and the doctors' opinions on the practical experience with the patients suggest the benefits of the provided solution.

Keywords: Parkinson's disease; deep learning; smart devices; freezing of gait

1 Introduction

Freezing of gait is a common symptom and severe complication, affecting every third patient with Parkinson's disease [1]. It is characterized clinically by sudden, relatively brief episodes of inability to produce effective forward stepping that typically occurs during gait initiation or turning while walking [2]. Parkison's disease is currently the second most common neurodegenerative disease [3], and many patients suffer from the freezing of gait symptoms. The estimated epidemiology of Parkinson's disease shows about 1% of people older than 60 years and up to 3% of people older than 80 years [3, 4]. The freezing of gait events often leads to falls, which cause serious injuries, significantly decreasing patients' quality of life [5]. As many authors agreed, treatment of freezing of gait is a challenging task.

Currently, medicine offers various ways to treat the freezing of gait, including drugs, surgery, and physiotherapy [6]. The most common way is the usage of Levodopa, which reduces the freezing of gait events. Unfortunately, this drug may cause a severe side-effect called dyskinesia, characterized by unwanted movements of patients' body parts [7-9]. Other treatment strategies are dopamine agonist or STN stimulation. Instead of many pharmacological strategies to manage the freezing of gait phenomena, the gait problems remain persistent for patients with Parkinson's disease [10].

Medication can effectively manage some symptoms of Parkinson's disease and improve the quality of life. However, symptoms like postural instability or gait impairments still cause unfortunate limitations [11, 12]. In addition to pharmacological methods, physiotherapy has become essential in treating Parkinson's disease patients in recent years. Many complications of Parkinson's disease are due to patients' muscle weakness, postural problems, and a general decline of physical activity [13]. This problem becomes more significant as the disease progress and motion abilities are getting worse, which causes the patient to have less and less physical activity [11].

Various approaches have been developed for gait rehabilitation in recent years, including individual, group, or home-based rehabilitation [14]. However, several authors agreed that home-based therapy could bring more injuries and falls and is ineffective in improving gait or balance [15-17]. An effective way to improve patients' walking ability appears in auditory and visual cueing [18]. The cueing is based on rhythmic visual or acoustic stimuli applied continuously or on-demand [19].

It is important to apply low-cost, widely used devices to make them available to home users. Mobile smart and wearable devices can be the right choice. Such devices are equipped with three-axis accelerometers, which can be used to detect the presence of freezing of gait. Anti-freeze aids can be divided into three main groups: visual, acoustic, and vibrational (tactile). All of them can be provided by a standard smartphone in conjunction with any other wearable device, such as smart glasses, smart watches, or headphones.

The presented paper discusses the possibilities of creating a home system for on-demand freezing of gait cueing, which can be a cheap and simple-to-use alternative to more complex systems. The paper begins with an overview of the related work in Section 2. We describe the current knowledge about walking freezes and their cueing using different approaches. The following section describes an experiment performed with patients to test devices in real conditions. In Section 4, we describe model training and the system architecture. Section 5 provides an evaluation of the experiments with patients and freezing of gait detection models, followed by conclusions of the paper.

2 Related Works

2.1 Cueing of Parkinson's Disease Patients

The reason why cueing works for Parkison's disease patients is still not fully understood. We can help patients using various types of different cues. The main idea is to provide sensory cueing based on rhythmic stimuli – acoustic, visual, or tactile. We can use simple metronome or rhythmic music for auditory stimulation. Usually, in studies, it is metronome beep in various ranges of frequencies from low frequencies with about 1 Hz [19] to high frequencies between 60 to 120 Hz [20]. Visual cues can be considered a wide range of regular patterns generated by digital devices or drawn on the floor [19, 21]. The tactile cues are rhythmic vibration impulses applied in low frequencies by wearable devices to any part of the patient's body (usually legs) [19]. In 2010, Bachlin and colleagues identified limitations with metronome cueing devices, such as those previously reported by Enzensberger et al., and Cubo et al. [38, 39]. When activated, these devices continually delivered auditory cueing regardless of whether freezing of gait was present or not. Cubo et al. identified this design limitation, reporting that patients may become habituated to the auditory stimuli, thus reducing the effect of cueing [39].

2.2 Cueing of Parkinson's Disease Patients by Wearable Devices

As Sweeney et al. show, many wearable devices for cueing freezing of gait symptoms have been built [22]. They found 4480 publications from January 2009 to December 2018, which contain Parkinson and Cue/cueing in its title. After a review process, they selected 18 publications that describe take-home systems for cueing Parkinson patients. Most of the reviewed works use continuous cueing, applied all the time. In the other cases, the authors provide the system that first detects freezing of gait events and applies on-demand cueing. The system usually uses more accelerometers placed on various parts of the user's body. One of the first works dealing with freezing of gait detection was Moore et al. [27]. The authors recorded 46 freezing of gait episodes during the experiment with eleven patients with idiopathic Parkinson's disease. Four of the patients does not show any freezing event during the experiment. The patients walk up to 100 m (based on their ability to walk). The patient's motion has been recorded by a 3-axis accelerometer placed on the patient's ankle with a frequency of 100 Hz. The work finds differences in dominant frequencies between freezing and regular gait events. The Freezing index, defined as a division of the area under the power spectra of 'freeze' band (3-8 Hz) by the square of the area under the spectra in the 'locomotor' band (0.5-3 Hz), can be then used to detect freezing of gait events. Based on the thresholds of the Freezing index, they were able to detect 78% of freezing of gaits events successfully, while the system also incorrectly labeled 20% of stand events as freezing of gait by global threshold. Lima et al. in [28] bring a detailed review of existing works focusing on freezing gait detection using wearable devices. The 27 works have been selected from PubMed and Web of Science databases. Four of them focus on falls and 23 on freezing of gait. The mentioned works use various sensors differently positioned on the patient's body. Only three of the mentioned works provide a system suitable for its use at home. The following Table 1 provides their overview, with the type of sensors and evaluation of detection results. As we can see, all these approaches only detect the events and none of them provide cueing functionality.

Table 1
Review of articles focusing on freezing of gait detection in the home environment [28]

Article	**Sensors**	**Location**	**Results**	**Cueing**
Rodríguez-Martín [29]	Accelerometer	Waist	Sensitivity: 91.7% Specificity: 87.4%	NO
Ahlrichs [30]	Accelerometer	Waist	Sensitivity: 92.3% Specificity: 100.0%	NO
Tzallas [31]	Accelerometer Gyroscope	Wrist Shin Waist	Accuracy 79%	NO

Thanks to the development of wearable visual headsets such as HoloLens or smart glasses, it has made it possible to create visual cues using wearable devices. One example of the use of HoloLens to guide freezing of gait was presented by Geerse et al. [32]. It is a solution called Holocue that displays 2D or 3D holographic elements for walking, as shown in Figure 1:

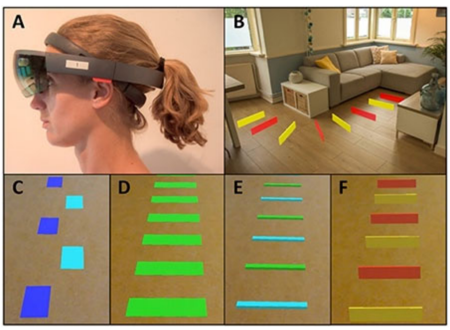

Figure 1
Holographic cues created by Holocue (source: [32])

According to [33], visual signals may be more effective than vibration or auditory. However, in [32], authors show that when wearable devices present visual stimuli, patients' immediate response generated by wearable devices worsens symptoms.

After several sessions, when patients became accustomed to wearing Holocue, the negative effect of Holocue disappeared but showed no significant improvement compared to control studies [32]. The Holocue solution offers an on-demand launch. However, it does not offer freezing of gait recognition, and a voice command triggers cueing. In addition to the mentioned solutions using wearable smart devices, even simpler solutions are already available. These simpler solutions use visual stimuli continuously, consisting of a laser lamp placed on boots or a wheelchair, as seen in Figure 2.

Figure 2
Simple solutions for visual FoG cueing (source: [35, 36])

Unfortunately, continuous application of the cues may reduce their performance during a time or cause cue addiction [19].

2.3 Machine-Learning Algorithms to Freezing of Gait Detection

Lima et al. in [28] state that most freezing of gait detection works with data from an accelerometer or inertial measurement unit (IMU) located on the ankle, knee, and belt. In addition, some work such as [37] use plantar pressure data recorded from users' shoes to detect freezing of gait. Many machine learning algorithms have been used to detect the events of freezing of gait. Random forests and Support Vector Machines (SVM) show good performance [38, 39]. Recurrent neural networks (RNNs) can perform better due to handling time-series data. Long Short Term Memory (LSTM) units have been invented to process data streams in neural networks. When training with acceleration data from three accelerometer sensors located on the knee, hip, and ankle, the network showed 83% accuracy in freezing gait detection [40]. Most research focused on participant-dependent models [35, 39, 40]. When FoG detection is performed on its wearable device, it is severely limited by the microcontroller's performance and memory size. Then, filtering, data pre-processing, and another high-performance task affect the detection time [37]. The scope of this paper is to overcome the performance limitations of wearable devices by using server-side detection. The second point is to improve patient comfort with a solution that uses only an ordinary smartphone placed in the patient's pocket without additional sensors on the feet or inside the shoe.

3 Setup of Aids Prototypes Testing with Patients

To verify the theoretical information mentioned in the introduction and its usability with available devices, we first tested cueing using wearable and smart devices with a small group of patients with Parkinson's disease.

We created a simple mobile application to test acoustic and tactile cues. The acoustic cues were applied using wireless headphones. The application makes metronome beeps in 60, 90, and 120 Hz frequencies. The vibration of the wearable watch has applied tactile cues placed on the patient's legs. It consisted of a short interval of vibrations in frequency based on the patient's standard gait period. We tried the period of patient native gait frequency, then half and quarter of this period.

The experiment was performed on the neurological clinic of University Hospital L. Pasteur in Košice. Patients were asked to participate in our experiment during the regular control visit. Those who agreed made several walks through our test trial path. The test trial consists of two walks through narrowed space and making two U-turns, where freezing of gait usually appears. The patient stood up from the chair, walked 4 meters in the first room, then walked through the door and continued 4 meters in the second room. After that, patients make a U-turn and continue back the same way. In the end, he should make a U-turn. Figure 3 depicts the visualization of the testing trial path. The total walk time and the number of freezing of gait occurrences were observed during the test walk. The medical specialist has counted the freezing of gait events.

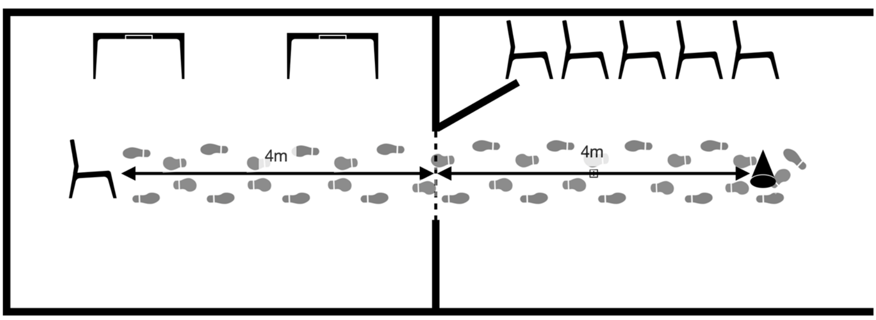

Figure 3

Visualization of the testing trial path walked by the patients

Tactile (vibration) and acoustic aids have been tested. During the test walk (first 4 meters usually without freezing of gait event), medical specialists measure the time and count the number of steps to get the patient's step period.

Then we added the smartwatch providing vibration aid onto the patient's wrist or ankle (the place with better sensitivity). We tested vibration aid with three periods - the base period of the patient's step and the half and quarter period of the steps period. The number of freezing episodes and time was measured using these aids.

We also tested acoustic aids on the same trial. As mentioned above, the acoustic aid was applied using wireless headphones, using simple beeps for selected frequencies of 60, 90, or 120 BPM. All these trials provided us with a dataset that showed practical usage of relatively cheap and usual devices (smartwatch with vibration ability, headphones) as tactile or acoustic cues for actual patients. We show the evaluation of the trial's results in Section 5.

4 Proposed System – Freezing of Gait Detection and Final System Architecture

After testing cues, we had a solid knowledge of how our tactile and acoustic aids work for the patients. We were able to design the final system architecture at this moment. Of course, we needed to work on a detection algorithm for freezing of gait (FoG) events for the final system setup. Therefore, this section describes the details on designed deep learning architectures for FoG detection, one of the proposed system modules. Then, we also added some details of the final system architecture itself.

4.1 Dataset for Detection of Freezing of Gait Events

Due to data-gathering issues through the COVID-19 pandemic with our pool of patients (testing of cues was shortly before pandemic), we decided to use the available dataset to design deep learning architecture to detect FoG events. The deep learning models trained on Parkinson's disease patients are expected to be transferable to new patients. To design and test the FoG detection algorithm, we used Daphnet Freezing of Gait Data Set [41], which contains more than 8 hours of walk data from ten patients. Eight of these patients experienced freezing of gait events during measurement. The professional physiotherapists identified 237 FOG events by video analysis. Three 3-axis accelerometers, placed on the patient's ankle, leg, and trunk, recorded data during the walking test trial in the laboratory. Data are sampled with a frequency of 64 Hz. Of course, we would like to use standard intelligent devices in our proposed system - smartphones, which are usually held in pockets. It supports our view to provide a solution as cheap as possible. It means that we can then minimize the need for placing any custom sensors. We use only data from the trunk sensor that are the same as data from smartphones in the pocket. Therefore, we will use only this part of the available dataset for learning, evaluation, and application for the deep learning architecture.

4.2 Deep Learning Architectures for Detection of Events

Contrary to most available works, we used data only from a sensor placed on the leg. This limitation may cause less accuracy of the FoG detection, but brings the pros that users do not need to wear any additional sensors than smartphones in their pocket. For FoG events recognition, we designed and tested different deep learning architectures.

For the primary reference on the foundations of neural networks and deep learning architectures, follow Goodfellow et al. in [42]. The usual architecture consists of some feature extraction and classification parts, where the second one is often realized as one or more fully connected feed-forward layers. For the extraction part in time series classification tasks, the main architecture types or elements within the neural network area include:

- Convolutional layers – a type of architecture often used for features extraction in image recognition extraction, but in a 1-D setup are also used to identify features from time series. Convolution 1-D layers are suitable for identifying local changes in time series.
- Long Short-Term Memory (LSTM) – recurrent network architecture for time series sequence learning, significantly better in learning longer relations between the elements within the series. Several extensions of the approach, like bidirectional LSTM, enhance features extraction from time series windows in both directions (forward and backward in time).
- Specific layers for preprocessing features – in time series, there are often some specific operations that are useful for extracting features, e.g., Fourier transformation, which helps for the analysis of frequencies. Such processing elements can also be applicable as a layer within the architecture [43].
- Hybrid architectures – a combination of previous architecture types (elements) within the one network.

We decided to combine such elements with another architectural idea used to improve classification and scalability in our work. It means that we combine parallel blocks within the architecture (with different setups in every block), producing one concatenated feature vector, followed by a fully connected part for final classification. This combined approach helps the classifier to enhance its granularity and robustness. The main idea comes from inception models from Google for more complex networks, which were introduced in [44], but we applied the principle for smaller networks. The main advantage of such architectures is that information is processed on different scales simultaneously within parallel blocks and their features are aggregated for one feature vector, which leads to better classification results and robustness of the models. We had a good experience with such architectures in other works in the domain of astrophysics, where we used it to classify eclipsing binary stars [45] or radio galaxies [46].

In the modeling phase, we used ReLU activation function in hidden layers and softmax for the output layer. We used categorical cross-entropy as a loss function and SGD as an optimizer. We compared four architectures to find the best for our purposes:

- **CNN model** – contains three parallel CNN (Convolutional Neural Network) blocks of layers with an input batch of 64 samples, each with three values. The CNN layers differ in the number of filters (20, 40, or 50). The output has two neurons with a soft-max activation function.
- **CNN + LSTM model** – has two parallel flows. One with CNN layer and the second with bidirectional Long Short-Term Memory layer.
- **2xCNN + LSTM model** – has three parallel flows. One block contains a bidirectional Long Short-Term Memory layer, and the second and third blocks contain the CNN layers. Same as in the first model, CNN-based blocks differ in the number of filters in layers.
- **Fourier + CNN –** adds to CNN model Fourier transformation as a pre-processing layer. Moore et al. in [27] found the importance of Fourier transformation in the detection based on frequency analysis.

4.3 Final System Architecture

It is essential to combine all the aspects mentioned above for practical application. Therefore, we proposed a cloud-based recognition system that connects acoustic or tactile aids. The cloud-based system enables the online model upgrade. The system consists of a mobile device as a sensor and an actuator for aids. As the first step, it is needed to label test data for a user, and then the system is able to work by itself.

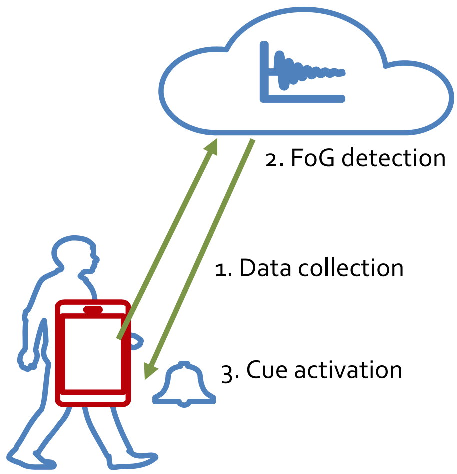

Figure 4
High-level architecture of the proposed system

Thanks to cloud-based messaging, the system may change the recognition system without changing any client application running on the user device. Figure 4 depicts the high-level architecture of the system.

The solution can be divided into two parts: server and client application. The client application runs on a smart device, which can be easily held in the patient's pocket. Because the recognition algorithm was developed for 64 Hz data, the mobile device must be compatible with the need for an acceleration sensor with a frequency of at least 64 Hz. According to the Android 12 Compatibility Definition document [47], it is strongly recommended that Android phones include an accelerometer sensor, which (if included) must provide data with a frequency of at least 100 Hz. The second requirement for the device is a functional internet connection. When no internet connection is available, the application does not offer a recognition feature.

The task of the client application is to record data from the accelerometer at the required frequency (for the presented models, it is 64 Hz). The recorded data are aggregated and sent as one batch (size N) to the server. FoG cueing is activated depending on the server response. After each N / 2 measurement, the batches are sent to improve performance and reduce response time. It means that for a batch of 64 samples (1 second at 64 Hz), we send data to the server every 32 new samples. One batch consists of N / 2 rows of old data (data used in the previous recognition), followed by N / 2 rows of new data. This halves the recognition time delay.

The server application uses a cloud platform as a service (PaaS) solution from a local provider running the Ubuntu operating system. The application is written in NodeJS and offers a Rest API. The Rest API offers a POST method at [host]/fog. The method accepts a json file containing the person's id and a recorded data, as the following code example shows:

```
{
   "person":12,
   "data": [
      [202,1803,386...],
      [292,1598,-49...],
      .....
   ]
}
```

The server provides a simple answer, containing a flag if the batch is FoG or not:

```
{
   "fog": true
}
```

After the API method is called, the server receives the data and evaluates the model. The machine learning operations run using the TensorFlow JavaScript machine learning solution. According to the person ID sent in the actual request, the correct TensorFlowJS model is loaded and evaluated using predict function applied to received values.

The solution with presented settings (64 Hz frequency and batch of 64 samples) creates requests up to 1.2 KB. The application makes two calls in one second. It creates a maximum of 2.4 KB (19.2 Kb) network traffic per second. This requirement can be met with huge reserve by the current mobile networks. If the number of clients connected to the server raises the required performance of the server application, it could be easily scaled thanks to using a SaaS cloud service.

5 Results and Evaluation

The success of the presented solutions depends on two of its abilities. The first is to provide cueing that effectively reduces the number of freezing of gait (FoG) episodes, shortens FoG time, or helps overcome it. The second is the use of a machine learning algorithm that is efficient enough to recognize an FoG episode and provide on-demand guidance.

5.1 Evaluation of Wearable Aids Testing

Eleven patients – four women and seven men with an average age of 66.44 years took part in the experiment. The average duration of patients' disease has been eight years. The acoustic and tactile cueing has been tested. Due to the motion limitation and fatigue, patients usually do not finish all tests. Two patients show no FoG events during the test walk. We excluded these patients from the evaluation.

We observed improvement in total walk time and the number of freezing of gait events during the test. The average total time of walk without any cueing was 42,43 ± 19,43 seconds, and the average number of FoG occurrences was 1,95 ± 1,27. As we mentioned before, the acoustic cueing was tested with three frequencies - 60, 90, and 120 BPM. There was a decrease in the number of FoG events and total walk time in all tested frequencies, leading to smoother and safer walks of the patients. The average reduction of occurrences of FoG events was about 60% in all three tested frequencies. However, the frequency of 120 BPM shows the best results in walking speeds (23,03%). Table 2 shows an overview of the results of acoustic aids.

Similarly to acoustic aids, we tested vibration aids on three different frequencies. The basic level is the patient's base step frequency (p). Then, the tested frequencies are p, p/2, and p/4. The number of tested subjects was lower than in acoustic aids testing. The main reason is that some patients had problems with sensitivity. We also issued problems with their fatigue after the previous testing. Table 3 depicts the results of the testing. We achieved the best results with the frequency of p/4, but only two people took part in the test with this setup. These people were patients in good conditions who were able to take part in all tests. The good health conditions of patients may affect the results. However, generally, we can see that vibration aids can significantly decrease the number of FoG events by at least 80%.

We can see different numbers of tested subjects for various frequencies. During experiments, not all patients could finish all experiments due to their physical abilities – fatigue or other complications. In these cases, we had to end measurements earlier. That caused the different number of patients in columns in Table 2 and Table 3. Average walk time is calculated from times for users who took part in the experiment with the required frequency. Average walk time with aids can be calculated as "Average walk time T" plus "Average decrease of T".

Table 2
Results of acoustic aids testing

	60 BPM	90 BPM	120 BPM
Number of tested subjects	5	8	6
Average walk time – T (seconds)	28,03	36,78	25,26
Average decrease of T (seconds)	2,51	5,63	7,35
Average decrease of T (%)	9,30	11,25	23,03
Average decrease of FoG (occurrences)	1,60	1,56	2,25
Average decrease of FoG (%)	64,28	62,50	58,33

Table 3
Results of vibration cueing

	p	p/2	p/4
Number of tested subjects	5	5	2
Average walk time – T (seconds)	34,12	35,21	26,23
Average decrease of T (seconds)	2,99	1,86	2,76
Average decrease of T (%)	5,88	2,45	11,09
Average decrease of FoG (occurrences)	1,4	1,4	1,5
Average decrease of FoG (%)	80	80	100

Due to the results of experiments, and according to theoretical background known from the literature, the designed acoustic and vibration aids show their usability for the proposed system.

5.2 Evaluation of FoG Recognition Algorithm

To evaluate FoG recognition models based on deep learning architectures, we used the following metrics:

- **Accuracy** = (TP+TN)/(TP+FP+FN+TN). It's the ratio of the correctly labeled subjects to the whole pool of subjects.
- **Recall** = TP / (TP+FN). Recall (sensitivity) is the ratio of the correctly positively labeled subjects by our models to all truly positive subjects.
- **Precision** = TP / (TP + FP). Precision is the ratio of the correctly positive labelled subjects by our models to all positive labelled subjects.
- **F1 score** = 2 * (Precision * Recall) / (Precision + Recall). It is the harmonic mean of the precision and recall.

where:

- **TP – True Positive -** event marked as FoG is really FoG,
- **TN – True Negative -** event correctly marked as normal gait,
- **FP – False Positive** – event marked as FoG, but is normal gait in reality,
- **FN – False Negative** – event is predicted to be normal gait but is FoG in reality.

The accuracy metric may be misleading for the unbalanced dataset. The freezing of gait (FoG) appears as a relatively short episode, interrupting the long duration of normal gait. Due to it, FoG datasets are strongly unbalanced. For practical application, the most crucial metric is recall. We considered as important to mark data batch as FoG also when it sometimes is marked as a false positive. In addition, we also considered precision and F1 score to take into account. The results showed significant differences between patients. Table 4 depicts personalized results for five selected patients from the dataset (who offer enough records).

Table 4

Personalized metrics of FoG class detection for every type of model. Bold marked numbers are the best results for five patients (S01-05). The results are considered for every batch of data separately.

3xCNN	**recall**	**precision**	**F1**
S01	38%	62%	47%
S02	62%	88%	73%
S03	50%	72%	59%
S05	39%	48%	43%
S07	7%	27%	11%

CNN + LSTM	**recall**	**precision**	**F1**
S01	36%	63%	46%
S02	**63%**	88%	**73%**
S03	51%	73%	60%
S05	21%	46%	29%
S07	5%	40%	8%
2xCNN+LSTM	**recall**	**precision**	**F1**
S01	51%	52%	52%
S02	62%	90%	73%
S03	**61%**	71%	**66%**
S05	30%	46%	37%
S07	12%	62%	20%
Fourier + CNN	**recall**	**precision**	**F1**
S01	**72%**	40%	**52%**
S02	44%	96%	60%
S03	56%	68%	61%
S05	**57%**	50%	**53%**
S07	**21%**	32%	**25%**

If we choose the same model architecture for all users, the average recall will be about 50%. However, if we use a personalized architecture and model with the best results for each user, we may achieve an average sensitivity of 55%. One of the problems with learning models and evaluation of results per batch is the small proportion of FoG events for patients in their data stream from the sensor. It varies from 5%-24%, where worse results are for the more imbalanced dataset because 5% means that only a small amount of batches had detectable events. It is especially a problem for S07 patient's data. For other patients, the average recall is better. While our solution shows lower sensitivity than other works, the deeper analysis showed some promising details:

- Again, it is essential to mention that we use only one sensor compared to the three used in most other works. Therefore, we provide a cheaper alternative for detection combined with an eventual type of aid (acoustic or vibration-based).

- For more balanced streams of data in the learning process, from patients with more than 15% and/or higher number of events in general, average recall of their personalized models for FoG batch detection is at least 65%.
- In a practical setup, FoG events in batches are not uniformly distributed but combined within one longer event (episode – more batches during some time). It means that there are more FoG batches in real life near each other, and with an average of 65% recall, it is possible to detect at least one FoG batch during the actual FoG event of a patient.

Especially the last observation has an important impact on practical implementation, when the achieved sensitivity for particular batches may be sufficient for the final usability of the system. It is important to note that the algorithm evaluates many batches during a single real-life FoG event (e.g., 20 batches for a 10 s FoG event). Figure 5 shows an example of five freezing events with a number of batches during every FoG event. One rectangle illustrates one batch as a one-second interval. The intervals overlap by 500 ms, increasing the number of batches and decreasing detection delay.

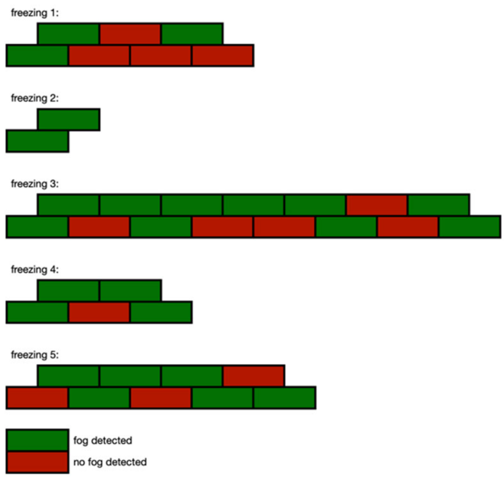

Figure 5

Test API calls for cueing with sample data from one of the patients for his FoG episodes. All rectangles are data batches recognized as FoG events by annotators. For every freezing event (even for their different length), our algorithm has several correct FoG detections, and API will start cueing the patient successfully.

In practice, we need to detect at least one of the first few batches during the FoG event to help overcome it for a workable solution. To try the performance in real conditions, we tested the system by calling created API function with sample data from the dataset. We found out, that in all of the FoG events, more than a half of batches in the event have been marked as a FoG. The visualization for one of the patient and his five freezing episodes is available in Figure 5. Thanks to detection of at least some of the batches from the start of the episode as FoG, our system will start cueing the patient after the first detection. Moreover, for most freezing episodes, the first detection is in one of the first batches, usually less than 1-2 seconds. Therefore, the presented solution will help the patient during the FoG episode with the current technological setup and detection algorithm while providing a cheaper solution for the system's sensor and cueing parts.

Conclusions

We proposed the system combining smart and wearable devices for detection of freezing of gait events of Parkinson's disease patients and their cueing using simple acoustic or vibration aids. Our experiments have shown that we can significantly improve walkability for patients suffering from the freezing of gait symptoms and improve their quality of life. The proposed system is one of the solutions to make a practical system based on cheap devices, which took part of life for almost everyone. Our detection algorithm has some limits, but it can still detect freezing of gait episodes soon after starting with only one sensor in mobile devices. It is the more convenient solution for patients because they only need their mobile devices. The medical assistant, who helped us with the experiments with patients during the experiment, also provided us with his feedback on the potential of the proposed solution: "…in comparison of acoustic and vibration aids, acoustic aids were more convenient for application and more convenient for patients. In the future, I would welcome the opportunity to install the application on a mobile phone for every patient with a stronger freezing of gait to improve their quality of life."

Acknowledgement

This work was supported by Slovak VEGA research grant No. 1/0685/21 and Slovak APVV research grant under contract No. APVV-17-0550. We would also like to thank medical specialists and patients from University Hospital L. Pasteur in Košice.

References

[1] Macht, M., Kaussner, Y., Möller, J. C., et al.: Predictors of freezing in Parkinson's disease: a survey of 6,620 patients, *Movement disorders* 22(7), 2007, pp. 953-956

[2] Nutt, J. G., Bloem, B. R., Giladi, N., et al.: Freezing of gait: moving forward on a mysterious clinical phenomenon, *The Lancet Neurology* 10(8), 2011, pp. 734-44

[3] Lee, A., Gilbert, R. M.: Epidemiology of Parkinson disease, *Neurologic clinics* 34(4), 2016, pp. 955-965

[4] De Lau, L. M., Breteler, M. M.: Epidemiology of Parkinson's disease, *The Lancet Neurology* 5(6), 2006, pp. 525-535

[5] Gao, C., Liu, J., Tan, Y., Chen, S.: Freezing of gait in Parkinson's disease: pathophysiology, risk factors and treatments, *Translational neurodegeneration* 9(12), 2020, pp. 1-22

[6] Nonnekes, J., Snijders, A. H., Nutt, J. G., et al.: Freezing of gait: a practical approach to management, *The Lancet Neurology* 14(7), 2015, pp. 768-778

[7] Schaafsma, J., Balash, Y., Gurevich, T., et al.: Characterization of Freezing of gait subtypes and the response of each to Levodopa in Parkinson's disease, *European journal of neurology* 10(4), 2003, pp. 391-398

[8] Fahn, S.: Does Levodopa slow or hasten the rate of progression of Parkinson's disease?, *Journal of neurology* 252(Suppl 4), 2005, pp. iv37-iv42

[9] Thanvi, B., Lo, N., Robinson, T.: Levodopa-induced dyskinesia in Parkinson's disease: clinical features, pathogenesis, prevention and treatment, *Postgraduate medical journal* 83(980), 2007, pp. 384-388

[10] Spaulding, S. J., Barber, B., Colby, M., et al.: Cueing and gait improvement among people wit Parkinson's disease: a meta-analysis, *Archives of physical medicine and rehabilitation* 94(3), 2013, pp. 562-570

[11] Chester, E. L., Turnbull, G. I., Kozey, J.: The effect of auditory cues on gait at different stages of parkinson's disease and during "on "/" off" fluctuations: a preliminary study, *Topics in Geriatric Rehabilitation* 22(2), 2006, pp. 187-195

[12] McNeely, M. E., Duncan, R. P., Earhart, G. M.: Medication improves balance and complex gait performance in Parkinson disease, *Gait & posture* 36(1), 2012, pp. 144-148

[13] Stelmach, G. E., Teasdale, N., Phillips, J., Worringham, C. J.: Force production characteristics in Parkinson's disease, *Experimental Brain Research* 76(1), 1989, pp. 165-172

[14] King, L. A., Wilhelm, J., Chen, Y., et al.: Effects of group, individual, and home exercise in persons with Parkinson disease: a randomized clinical trial, *Journal of Neurologic Physical Therapy* 39(4), 2015, pp. 204-212

[15] Schenkman, M., Hall, D. A., Barón, A. E., et al.: Exercise for people in early- or mid-stage Parkinson disease: a 16-month randomized controlled trial, *Physical therapy* 92(11), 2012, pp. 1395-1410

[16] Canning, C. G., Allen, N. E., Dean, C. M., Goh, L., Fung, V. S.: Home-based tread-mill training for individuals with Parkinson's disease: a randomized controlled pilot trial, *Clinical rehabilitation* 26(9), 2016, pp. 817-826

[17] Quinn, L., Busse, M., Khalil, H., et al.: Client and therapist views on exercise programmes for early-mid stage Parkinson's disease and Huntington's disease, *Disability and rehabilitation* 32(11), 2010, pp. 917-928

[18] Picelli, A., Camin, M., Tinazzi, M., et al.: Three-dimensional motion analysis of the effects of auditory cueing on gait pattern in patients with Parkinson's disease: a preliminary investigation, *Neurological Sciences* 31(4), 2010, pp. 423-430

[19] Velik, R.: Effect of on-demand cueing on freezing of gait in Parkinson's patients, International Journal of Biomedical Engineering 6, 2013, pp. 280-285

[20] De Icco, R., Tassorelli, C., Berra, E., et al.: Acute and chronic effect of acoustic and visual cues on gait training in Parkinson's disease: a randomized, controlled study, *Parkinson's Disease* 2015, article id 978590, 2015, pp. 1-9

[21] Janssen, S., Bolte, B., Nonnekes, J., et al.: Usability of three-dimensional augmented visual cues delivered by smart glasses on (freezing of) gait in Parkinson's disease, *Frontiers in neurology* 8:279, 2017, pp. 1-10

[22] Sweeney, D., Quinlan, L. R., Browne, P., et al.: A technological review of wearable cueing devices addressing freezing of gait in Parkinson's disease, *Sensors* 19(6):1277, 2019, pp. 1-35

[23] Bächlin, M., Plotnik, M., Roggen, D., et al.: A wearable system to assist walking of Parkinsons disease patients, *Methods of information in medicine* 49(1), 2010, pp. 88-95

[24] Samà, A., Pérez-López, C., Rodríguez-Martín, D., et al.: A double closed loop to enhance the quality of life of Parkinson's Disease patients: REMPARK system, *Studies in health technology and informatics* 207, 2015, pp. 115-124

[25] Mazilu, S., Blanke, U., Dorfman, M., et al.: A wearable assistant for gait training for Parkinson's disease with freezing of gait in out-of-the-lab environments. *ACM Transactions on Interactive Intelligent Systems*, 5(1), article no. 5, 2015, pp. 1-31

[26] Ahn, D., Chung, H., Lee, H. W., et al.: Smart gait-aid glasses for Parkinson's disease patients, *IEEE Transactions on Biomedical Engineering* 64(10), 2017, pp. 2394-2402

[27] Moore, S., MacDougall, H., Ondo, W.: Ambulatory monitoring of freezing of gait in Parkinson's disease, *Journal of Neuroscience Methods* 167, 2008, pp. 340-348

[28] De Lima, A. L. S., Evers, L. J., Hahn, T., et al.: Freezing of gait and fall detection in Parkinson's disease using wearable sensors: a systematic review, *Journal of neurology* 264(8), 2017, pp. 1642-1654

[29] Rodríguez-Martín, D., Samà, A., Pérez-López, C., et al.: Comparison of Features, Window Sizes and Classifiers in Detecting Freezing of Gait in

Patients with Parkinson's Disease hrough a Waist-Worn Accelerometer, *Frontiers in Artificial Intelligence and Applications* 288, 2016, pp. 127-136

[30] Ahlrichs, C., Samà, A., Lawo, M., et al.: Detecting freezing of gait with a tri-axial accelerometer in Parkinson's disease patients, *Medical & biological engineering & computing* 54(1), 2016, pp. 223-233

[31] Tzallas, A. T., Tsipouras, M. G., Rigas, G., et al.: PERFORM: a system for monitoring, assessment and management of patients with Parkinson's disease, *Sensors* 14(11), 2014, pp. 21329-21357

[32] Geerse, D. J., Coolen, B., Hilten, J. J., Roerdink, M.: Holocue a Wearable Holographic Cueing Application for Alleviating Freezing of Gait in Parkinson's Disease, *Front. Neurol.*, 2022

[33] Cole, B. T., Roy, S. H., Nawab, S. H.: Detecting freezing-of-gait during unscripted and unconstrained activity, *Proceedings of 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 2011, pp. 5649-5652

[34] Rezvanian, S., Lockhart, T. E.: Towards real-time detection of freezing of gait using wavelet transform on wireless accelerometer data, *Sensors* 16(40):475, 2016, pp. 1-11

[35] Donovan, S., Lim, C., Diaz, N., et al.: Laserlight cues for gait freezing in Parkinson's disease: An open-label study. *Parkinsonism & Related Disorders 17,* 2011, pp. 240-245

[36] Roberts, J.: Shoe-mounted laser to 'unfreeze' people with Parkinson's scoops €1 million prize, *Horizon The EU Research & Innovation Magazine,* 2019 (online: https://ec.europa.eu/research-and-innovation/en/horizon-magazine/shoe-mounted-laser-unfreeze-people-parkinsons-scoops-eu1-million-prize, available: 12.9.2022)

[37] Shalin, G., Pardoel, S., Lemaire, E. D. et al.: Prediction and detection of freezing of gait in Parkinson's disease from plantar pressure data using long short-term memory neural-networks. *J NeuroEngineering Rehabil 18*, 2021

[38] Samà A., Rodríguez-Martín D., Pérez-López C., et al.: Determining the optimal features in freezing of gait detection through a single waist accelerometer in home environments. *Pattern Recognit Lett*. 2018; pp. 135-143

[39] Mazilu S., Hardegger M, Zhu Z., et al.: Online detection of freezing of gait with smartphones and machine learning techniques: 6th International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health) and Workshops 2012, pp. 123-130

[40] Ashour A. S., El-Attar A., Dey N., Abd El-Kader H., Abd El-Naby M. M.: Long short-term memory based patient-dependent model for FOG detection in Parkinson's disease. *Pattern Recognit Lett*. 2020; pp. 23-29

[41] Bachlin, M., Plotnik, M., Roggen, D., et al.: Wearable assistant for Parkinson's disease patients with the freezing of gait symptom, *IEEE Transactions on Information Technology in Biomedicine* 14(2), 2009, pp. 436-446

[42] Goodfellow, I., Bengio, Y., Courville, A.: Deep Learning. MIT Press, 2016

[43] Pratt, H., Williams, B., Coenen, F., Zheng, Y.: FCNN: Fourier Convolutional Neural Networks, *Lecture Notes in Computer Science* 10534, Machine Learning and Knowledge Discovery in Databases, 2017, pp. 786-798

[44] Szegedy, C., et al.: Going deeper with convolution, *Proceedings of the IEEEconference on computervision and pattern recognition*, 2015, pp. 1-9

[45] Cokina, M., Maslej-Kresnakova, V., Butka, P., Parimucha, S.: Automatic classification of eclipsing binary stars using deep learning methods, *Astronomy and Computing* 36, art. no. 100488, 2021, pp. 1-12

[46] Maslej-Kresnakova, V., El Bouchefry, K., Butka, P.: Morphological classification of compact and extended radio galaxies using convolutional neural networks and data augmentation techniques, *Monthly Notices of the Royal Astronomical Society* 505(1), 2021, pp. 1464-1475

[47] Google LLC: Android 12 Compactibility Definition, 2021, pp. 92-93