Mind the Steps

Towards Auditory Feedback in Tele-Rehabilitation Based on Automated Gait Classification

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ABSTRACT

We describe a proof-of-concept for the implementation of a mobile auditory biofeedback system based on automated classification of functional gait disorders. The classification is embedded in a sensor-instrumented insole and is based on ground reaction forces (GRFs). GRF data have been successfully used for the classification of gait patterns into clinically relevant classes and are frequently used in clinical practice to quantitatively describe human motion. A feed-forward neural network that was implemented on the firmware of the insole is used to estimate the GRFs using pressure and accelerator data. Compared to GRF measurements obtained from force plates, the estimated GRFs performed highly accurately. To distinguish between normal physiological gait and gait disorders, we trained and evaluated a support vector machine with labeled data from a publicly accessible database. The automated gait classification was sonified for auditory feedback. The high potential of the implemented auditory feedback for preventive and supportive applications in physical therapy, such as supervised therapy settings and tele-rehabilitation, was highlighted by a semi-structured interview with two experts.

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CCS CONCEPTS

• **Applied Computing**; • **Health Informatics**; • **Sound and Music Computing**; • **Human-centered Computing Computing**; • **Sound-based input / output**;

KEYWORDS

Auditory Feedback, Automated Gait Classification, Physical Therapy, Biomechanics, Rehabilitation

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1 INTRODUCTION

Age-related physiological changes go hand in hand with a physical decline that significantly impacts the gait pattern and fall risk in the elderly population. Staying active is a crucial factor to counteract this process and prevent age-associated autonomy loss. Thus, measures are needed that support this age group in maintaining their ability to walk and leading an active lifestyle in the long-term [5].

Methods for detecting and assessing gait impairments range from traditional apparent diagnoses by medical experts to sophisticated technical procedures based on motion capturing systems and measurements with force plates to analyze kinematic and kinetic gait characteristics. Apart from their obvious advantages, these methods come with disadvantages as well. For example, apparent therapeutic diagnosis, often supported by video recordings [18], is susceptible to human error and subjective judgement. While 3D motion capture devices including multi-camera systems and force plates are the gold standard for human gait and motion analysis, they are quite expensive and entail time-consuming procedures significantly limiting their widespread use and availability [45]. The biggest downside of these systems is that they can only be operated in laboratory environments and are therefore not suitable for recording the actual walking behavior of a person in his or her everyday environment [23]. If the gait patterns recorded in the gait laboratory deviate beyond a certain tolerance from a person's movement behavior in everyday life, this can also lead to incorrect diagnoses and inadequate treatment measures. In order to solve this problem, an early diagnosis of deviations from physiological (i.e. "normal") gait patterns as well as adequate preventive and therapeutic measures for gait training are essential for potentially affected people. Motor learning and gait re-education usually requires feedback that is often provided by either therapists or by special measurement systems using visual, auditory, haptic, and multimodal feedback strategies [41]. Under laboratory conditions, however, the frequency of providing feedback and its modes of application are limited. Simple mobile systems are needed to provide feedback for everyday situations beyond therapy settings and laboratory equipment [34]. Such systems need to be tailored to the customer demands. That is particularly necessary for elderly patients so that systems provide easy-to-use feedback and can be deployed independently by the users.

We describe a proof-of-concept approach for the implementation of a mobile auditory biofeedback system based on automated classification of functional gait disorders (GD). The implementation is embedded in a sensor-instrumented insole (equipped with pressure and accelerator sensors) which was classified as a medical device in the course of this research and is now available on the market. Our scoping study aims to investigate (1) the feasibility of the approach and (2) to assess its potential for preventive and supportive applications in physical therapy, such as supervised therapy settings and tele-rehabilitation ("therapy@home" as suggested by [48, 49]).

Our proof-of-concept approach includes the following steps: First, we obtained simultaneous records of ground reaction force (GRFs) measurements and data from mobile sensor-instrumented insoles used by 48 healthy volunteers while walking (Section 3.2). GRF data have been successfully used for the classification of gait patterns into clinically relevant classes and are frequently used in clinical practice to quantitatively describe human motion [1, 31, 44]. In contrast to force plates, however, mobile insoles only measure pressure distribution alongside other aspects such as velocity and acceleration (e.g., via embedded IMUs). In a second step, we therefore evaluated different machine learning-based approaches to estimate GRFs based on the pressure and accelerometer data from the insole device (Section 3.3). To distinguish between "normal" physiological gait (NG) and GD, we then trained and evaluated a support vector machine (SVM) with labeled data from a publicly accessible database [44] (Section 3.4) in a third step.

Finally, we describe a sonification model providing auditory feedback according to the automated gait classification. Due to the scope of the project and the fact that at the time of our experiments, the insole had not yet been classified as a medical device, an evaluation including patients with GD was not possible. Therefore, we evaluated the approach using only healthy gait patterns (Section 3.5). To assess the impact and potential of the auditory feedback for

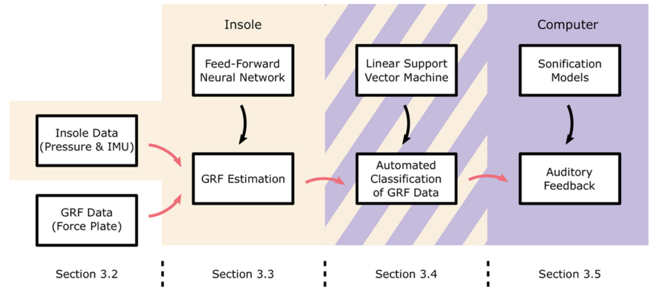

Figure 1: Approach as described in Sections 3.2 to 3.5.

physical therapy despite this constraint, we present an extension of our approach by a user-centered scenario with an automated classification of up to three gait and posture patterns (Section 4). The assessment through expert interviews is presented in Section 5. Section 6 provides an overview of possible future applications.

2 RELATED WORK

Biofeedback is a frequently used tool in clinical settings to assist motor learning and re-education. On the one hand, it allows to create an awareness of deviating aspects, while on the other hand, it helps with the rehabilitation process. This feedback is ideally provided by professionals such as physical therapists and is usually communicated verbally, visually, or tactilely [28]. However, lasting changes in movement behavior require regular practice over time and continuous feedback to internalize them. Therefore, it is crucial that patients with GD practice independently and beyond the therapy setting (therapy sessions usually take place at weekly intervals) [34] and receive immediate feedback on their walking behavior. A special method is the acoustic representation of motion sequences by means of real-time sonification [15, 40, 46, 47], as it is implemented in the field of gait analysis, especially in combination with sensor-equipped insoles [2, 23]. The integrated sensor technology allows cost-effective and wireless data transmission to stationary or web-based servers and mobile devices [49]. As a result, numerous products - ranging from prototypical approaches to market maturity - have been realized in recent years that are mobile and sufficiently powerful to be used as auditory feedback systems in everyday life as well as in clinical rehabilitation [23, 24, 37].

In sports [15, 36, 40] as well as in rehabilitation [17, 19, 34], the effectiveness of sonification for control and (re-)learning of motor functions has already been demonstrated. The complexity of the implementations varies widely. In the field of gait rehabilitation, it ranges from systems that support heel strike by a simple synthetic click to sonic representations of the swing phase while walking [2, 23, 24].

To some extent, these systems are already capable of making users more aware of their gait behavior through auditory feedback, thereby supporting motor learning processes [23]. In order to apply them as a comprehensive diagnostic tool in gait analysis, mobile monitoring of GRFs for the purpose of feedback could be of great value. Considered as a well-established standard in gait analysis [24], GRFs are familiar indicators for clinical experts. The GRF vector is composed of the vertical (GRF_V), anteroposterior (GRF_{AP}), and mediolateral (GRF_{ML}) force components, which are generally determined using force plates. For the calculation of GRF data using sensor-equipped soles, several approaches will be presented in the following.

The mobile measurement of GRFs that is comparable to force plates in terms of the method used is only possible with "outsoles", which are attached as a second sole underneath the actual shoe sole and can thus record the reaction forces of the ground [32]. Such systems are quite vulnerable to the impact of intruding dirt and are too expensive for everyday use [12]. Unlike outsoles, soles implemented inside shoes (insoles) do not have direct contact with the ground. In addition to optical [11], capacitive [35] or foam sensors [38], pressure sensors are used in most cases to determine the pressure distribution during standing or walking [12, 24]. Various authors achieve an approximate estimation of effective GRFs using insole pressure data in combination with additional visual motion analysis [10] or adaptive pattern recognition algorithms [39]. Approaches that perform an algorithmic categorization of gait patterns based on insole data have also shown promising results [20, 50].

The use of insoles with and without auditory feedback has been investigated in several research approaches [4, 16, 21, 24–26, 29, 32, 42]. To our best knowledge, however, there has been no approach that combines an embedded gait classification system with auditory feedback on a medically approved insole.

3 GAIT MEASUREMENT AND CLASSIFICATION USING INTEGRATED INSOLE DEVICES

In this chapter, we present an overview of the used insole including its technical configuration and functionality as well as a detailed view of the GRF estimation and automated gait classification.

3.1 Design of the Sensor-Instrumented Insole

The insole was developed by one of the project partners and originally designed as a multiple-sensor insole for everyday use in combination with a cloud-based application for mobile devices. To make the device accessible to a large customer base, a retail price of approximately 300 euros for a pair of insoles was targeted. Meanwhile, the insole has been certified as a class 1 medical device (93/42/EWG-Medical Device Directive MDD).

The version of the insole used in the presented approach is instrumented with twelve textile pressure sensors per insole and additional IMU sensors, out of which the 3-degrees-of-freedom (3DOF) accelerators in each insole are used for measurements. Sensor data can be recorded to an internal flash drive at sample rates of 50 to 100 samples per second. Additionally, data are transmitted via Bluetooth Low Energy (BLE 4.2) to a PC software at 100 samples per second. Besides raw sensor data, the data stream also includes the estimated GRFs, center of pressure (COP), and class estimation that have been developed and implemented within our approach (Sections 3.3 & 3.4). The PC software includes a visualization of parameters such as pressure distribution or COP (see Figure 2), and forwards all incoming data to an Open Sound Control (OSC) stream for further utilizations, i.e., auditory feedback.

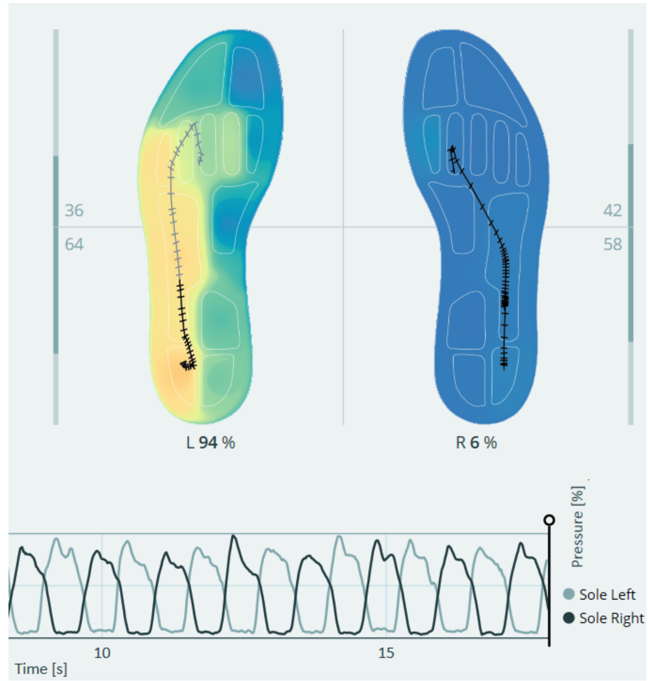

Figure 2: Graphical user interface of the PC software used with the insoles. The figure shows the pressure map for both insoles as well as the path of the center of pressure during a step.

3.2 Gait Recordings on Insoles and Force Plates

As a reference for the estimation of the GRFs obtained from the insole sensor data, a set of 828 steps from 18 male and 30 female healthy participants[1] are recorded on a ten-meter walkway using a force plate (type 9286B, Kistler GmbH) sampled at 300 Hz and the above-described insole sampled at 100 Hz (see Figure 3). The participants were required to walk in standardized sneakers (Nike SB Check solar) equipped with the insole at a self-chosen walking speed. Five to eight valid force plate hits of the dominant leg were recorded using Vicon Nexus (v. 2.9, Vicon Motion Systems Ltd UK). The raw data from the force plate (GRFs) and the insoles are preprocessed (filtering and normalization) in Matlab (v. 2019b, The Mathworks, Inc).

3.3 Implementation of a Neural Network for GRF Estimation

To calculate and estimate GRFs from the insole data we tested and compared different neural network (NN) architectures including a feed-forward neural network (FFNN) [43], a wavelet neural network (WNN) [42], and a long short-term memory network (LSTM) [53][2].

[1] Average (Standard Deviation): age = 38.8 (10.3) years, weight = 73.6 (13.2) kg, heigth = 172.8 (8.8) cm, shoe size 41.2 (2.3) EU.

[2] The NNs have been tested with multiple configurations of hidden layers and numbers of nodes. For the WNN, we used one wavelet layer with the size of 25, and for the LSTM one layer with 25 hidden units. In the end, an FFNN with one hidden layer and 25 nodes was implemented.

Figure 3: Parallel recording of force plate and insole data with additional motion tracking.

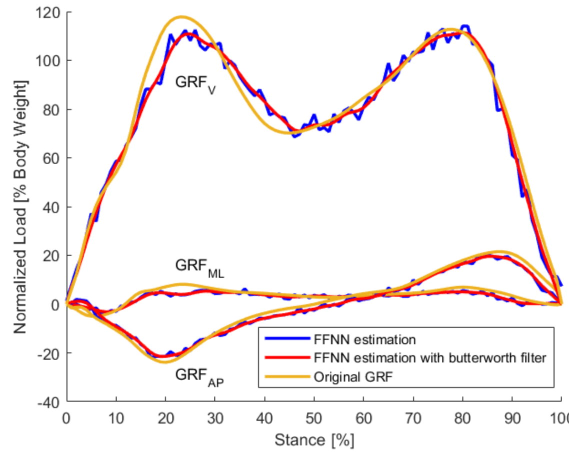

Figure 4: A comparison of the estimated GRF components with (red) and without post-processing (blue) predicted by an FFNN and the original GRF data obtained from a force plate (yellow).

Single steps of the force plate recordings (see Section 3.2) served as ground truth for the training and evaluation of these NNs. The recorded steps of the insole were synchronized by timestamps to the GRFs obtained from the force plate. To reduce complexity and calculation time, data of the seven pressure sensors placed at the forefoot and the five pressure sensors at the mid-rear foot were weighted and added up resulting. We utilized these two aggregated signals in addition to the 3DOF accelerator data and the step length as input to the NNs. To compensate for varying step durations, the data of each step were normalized to 101 data points (100% stance).

The output layer of the NNs was set to a fixed number of data points (101) for each component of the GRF. A low-pass Butterworth filter of the 2nd order with a cut-off frequency at 40Hz and 20Hz was used to smooth the estimated signals [52]. Figure 4 shows a comparison of the estimated GRF components with and without the use of this post-processing step and the original GRF components obtained with the force plate.

For the experiments, the dataset was split into a training (90%) and a test set (10%) in such a manner that data from the same participant could not be in both sets. The training set serves to train the NNs, whereas the test set is used to evaluate the generalization ability of the trained models and to compare the different NN architectures. The partitioning of the data was performed several times to provide a robust evaluation value of the normalized root mean square error (NRMSE).

The results in Table 1 show that for all examined architectures GRF$_V$ and GRF$_{AP}$ are relatively well estimated, while GRF$_{ML}$ proves to be the most difficult component to model. The simpler models, i.e., FFNN and WNN, perform better on all components, as they seem to cope better with smaller datasets. The small amount of data does not seem to have been sufficient to train robust LSTMs.

In addition to performance, resource constraints in the insole are also an important consideration when selecting an NN architecture. Therefore, we decided to implement FFNN models in the firmware of the insole, as they have the smallest number of parameters and thus require the least amount of memory. An FFNN was implemented for each of the three GRF components. These models provide estimates of the individual components after each step.

The first phase, i.e., the evaluation of the different models, was performed in Matlab 2019b (MathWorks, USA), while the subsequent implementation in the firmware of the insole was carried out in the programming language C.

3.4 Automatic Classification of Physiological and Atypical Gait Patterns

To classify the estimated GRF data from the pressure insole into physiological and pathological gait patterns, another machine learning model was trained based on the publicly accessible GaitRec GRF dataset [22]. It comprises GRF measurements from 2,084 patients with various musculoskeletal impairments and data from 211

Table 1: Results (obtained from different test datasets) in terms of the normalized root mean square error for the estimation of the three GRF components from insole data with the feed-forward neural network (FFNN), the wavelet neural network (WNN), and the long short-term memory network (LSTM).

Component	FFNN	WNN	LSTM
GRF$_V$	3.95 ± .47%	3.94 ± 0.47%	5.42 ± 0.64%
GRF$_{ML}$	9.49 ± .56%	9.44 ± 1.70%	9.25 ± 1.40%
GRF$_{AP}$	3.81 ± .55%	3.86 ± 0.55%	5.12 ± 0.70%

healthy control subjects. This dataset is the largest and, in terms of pathology, the most diverse dataset available to date.

A balanced subset (on the subject, trial, and pathology levels) was randomly generated from the overall dataset. This subset includes partitioning the data into a physiological and a pathological class, each containing data from 180 individuals. For each person, six trials are selected randomly resulting in a total of 2,160 trials. Using the predefined training and test split from the GaitRec dataset, the balanced training and test sets used for this study comprise 1,584 and 576 trials, respectively.

Due to promising results of approximately 91% classification accuracy on a similar dataset [44], an SVM with a linear kernel was implemented for the underlying classification task using the LIBSVM library [8]. First, a hyperparameter tuning was conducted in the form of a five-fold cross-validation on the training data. After finding the best hyperparameters, the linear SVM was trained on the whole training data and evaluated on the unseen test data. While using all three GRF components for the training of the SVM, the GaitRec test data were correctly classified with an accuracy of 91%. As an additional evaluation step, all estimated physiological GRFs from the FFNN models (see Section 3.3) were classified using the same SVM model and achieved an accuracy of 97%.

In a final step, this pre-trained SVM was transferred to the firmware of the insoles by implementing the detection function as described in [7, eq. 61].

3.5 Auditory Feedback

In a former study on auditory feedback of plantar pressure distributions provided by sensor instrumented insoles [23], we compared sonification models representing ankle-foot-rollovers based on several synthesis algorithms and and showed their impact on the gait behaviour of the test participants. For an auditory feedback that represents classification estimates, i.e. static states, more simplistic sonification models seem suitable.

With reference to the work of Biesmans and Markopoulos [4], we followed a design that supports users to rely on their own proprioception by providing a minimum of auditory information. This was achieved through an event-based sonification that only responds to changes of the classification estimate (threshold) from NG to GD or vice versa.

For the sonification application, we used the MAX8 programming environment[3] which – due to its dataflow-oriented programming paradigm – is particularly suitable for prototype implementations in the field of auditory display. The incoming data stream from both insoles was transmitted via OSC (see Section 3.1) including raw sensor data as well as estimated classification labels (distinguishing between NG and GD). Regarding a target group that includes elderly users, the auditory feedback was designed to be easy to understand, pleasant and adjustable (pitch, sequence, duration, loudness) to individual needs. For the feedback, two acoustic events are needed: one triggers an ascending three-tone sequence (see Table 2) synthesized by a guitar-like Karpus-Strong implementation (positive feedback), when the decision of the SVM changes from GD to NG; and a second one in the case of a change back to GD. In this case, a descending three-tone sequence (negative feedback) is played. It is noteworthy that only changes of the classes (i.e., states) cause an acoustic event. Additional reverb is used to smoothen the signals.

[3]www.cycling74.com

Table 2: Auditory feedback of automated gait classification. Decision change to physiological gait (NG) results in positive feedback, a change to atypical gait (GD) is represented by negative feedback.

Sonification	Synthesis	Auditory feedback	
		negative	positive
Single Sound (playback on state changes)	**guitar** (Karpus-Strong)	descending 3-tone sequence (F5, D5, B4 in 200ms)	ascending 3-tone sequence (C4, G4, C5 in 200ms)

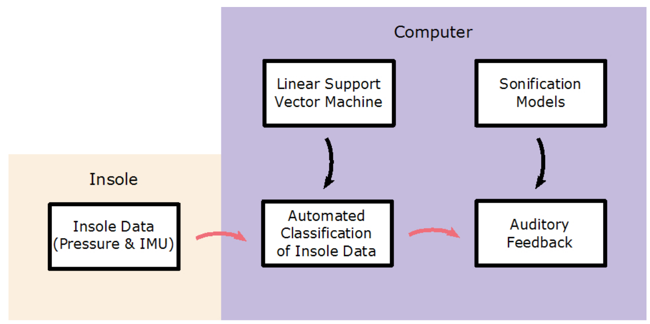

Figure 5: Implementation of user-centered training.

4 USER-CENTERED TRAINING

To achieve the second aim of our scoping study[4], we pursued an alternative approach to obtain meaningful expert feedback and focus on a user-centered setup. We used the raw sensor data from the insole and integrated a linear SVM [6, 9, 14] as a classifier into the sonification application (see Figure 5). This model can be trained individually for a specific user to classify certain gait patterns, e.g., as correct or incorrect. The input data consist of 15 features (12 pressure sensors and three accelerometer axes) for each sample, which is recorded at a sample rate of 25 samples per second. Through a graphical user interface, the operator records the insole data and immediately trains the model with these data and the associated ground truth label. After training the model with the user's data, different sonification models can be associated with the different labels for online feedback. The SVM has shown a good performance when classifying data with a limited number of training samples.

The model was also successfully trained and tested with static postures in simple exercises such as a lunge or squat where the model was able to detect weight shifts from the lateral ("outer") to the medial ("inner") side of the foot (and vice versa). During these

[4]Assessing the potential of auditory feedback based on automated gait classification for preventive and supportive applications in physical therapy.

Table 3: Continuous auditory feedback displaying two-fold deviations (x_1, x_2) from "normal" state x_0. A wind and a trumpet model can be alternatively selected.

Sonification	Synthesis	Auditory Feedback	
		deviation state x_1	deviation state x_2
Continuous Sound (deviations from "normal" state x_0 sound permanently)	**wind** modulating (subtractive synthesis) **trumpet** slightly modulating (FM synthesis)	low frequency components (howling) lower pitched (200 Hz)	high frequency components (whistling) higher pitched (300 Hz)

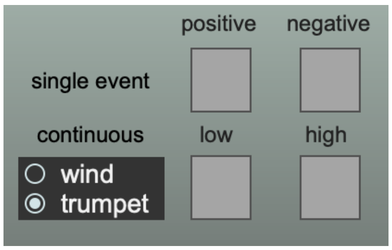

Figure 6: Section of the user interface. Classes can be linked to single events (positive or negative feedback) or continuous feedback with concrete (wind) or abstract (trumpet) sounds.

exercises, a physical therapist is especially interested in supporting the patient in distributing more weight to the lateral side of her or his foot, thereby maintaining a neutral frontal alignment of the knee. If the patient puts more weight over the medial side of the foot, there is a high risk of increasing unfavorable loads to the knee. To provide adequate auditory feedback for the lateral and medial weight shifts, the sonification model described in the previous section was extended by two variants of continuous feedback representing a wind (concrete) and a trumpet metaphor (abstract). The wind sound, based on the model by Farnell [13], is implemented in a howling and a whistling version, which can be clearly distinguished. The alternative trumpet tones (low/high) are created through FM synthesis. Following the attack and decay phases, it reaches a soft sustain phase, which sightly modulates (see Table 3).

With the implemented continuous feedback, it is now possible to display two-fold state deviations (e.g., medial and lateral weight shifts) from normal state or NG independently. This is an important aspect, since people may respond to auditory feedback (howling wind) on a deviation by overcompensation (e.g., deviation in the opposite direction). In this case, a second sound (whistling wind) is used to indicate this. Figure 6 gives an overview of the possible combinations of the two sonification approaches. All components besides the wind/trumpet selection can be arbitrarily activated.

5 ASSESSEMENT BY PHYSICAL THERAPISTS

To evaluate our first prototypes of automated auditory feedback, we conducted a semi-structured interview with two physical therapists (1 female and 1 male, with 7 and 28 years of experience) from our institution. Both therapists were not associated with the project. The meeting lasted two hours and encompassed:

(a) an introduction to the approach, its functionality and the intended target group;

(b) a demonstration session including two scenarios: (1) recording and training of two walking states (physiological and lateral load) by one of the team members, including testing based on real-time changes of gait behavior, (2) recording and training of three posture states (normal standing, and standing with weight distributed to the medial or lateral aspect of the foot), including testing on the basis of real-time changes of load shifting, and

(c) an overall discussion and evaluation of the potential of the approach for application as a preventive and supportive tool for physical therapy and tele-rehabilitation.

Both experts agreed that they could clearly distinguish between all the auditory feedback implementations and attribute them to the observed gait behavior. The wind noise associated with the external load was clearly recognizable and attributable to the gait behavior by the experts. The method offers a lot of potential and is particularly useful at the beginning of treatment. The trumpet sounds were also clearly attributable to the gait behavior by the experts. They were initially perceived as more pleasant than the wind sounds. According to the experts, however, the trumpet sounds can be expected to be more intrusive than the wind sounds with longer-lasting tests. Wind in general was negatively connoted by one expert who suggested that there should be several sounds for a user to choose from. Sounds should always be perceived as pleasant (and not as a punishment) for therapy to be successful.

Both physical therapists found continuous auditory feedback easier to comprehend than the event-based sonification that they had previously heard. The ascending and descending three-tone sequences of the event-based sonification were perceived as rather complex, particularly with respect to the cognitive workload imposed on elderly people. Generally, pre-testing of the perceptional abilities of prospective patients was recommended by both experts.

During the observation, the experts noted that compensatory movements could be triggered in response to auditory feedback. After all, the absence of an auditory signal[5] would not mean that the response resulted in a physiological gait pattern. The following demonstration, in which three static postures were trained, offered a first approach to make compensatory movements audible.

In conclusion, the two experts suggested that a procedure for future implementations in the field of physical therapy should begin with an initial placement test and that the difficulty of the static positions should be gradually increased, since the therapy setup

[5] In a setup with continuous feedback on one-directional deviations.

focuses more on static positions, which are usually faster and easier to interpret.

6 POTENTIAL FOR FUTURE APPLICATIONS & TREATMENTS OF PATHOLOGIES

Gait-related pathologies can affect all age groups and range from traumatic and neurological to geriatric patients. The availability of various tools allows the best possible support for patients during the rehabilitation process and assistance in achieving the specified therapy goal. In the shared decision-making process, different therapy options and therapeutic appliances must be discussed with the client, that are feasible and fit the clients' expectations [3]. There are also strategies needed to provide support to clients in rural communities with a shortage of health care professionals [51] or special circumstances like pandemic-induced contact restrictions [30].

One focus of this project was to combine a mobile gait classification system with auditory feedback. A future application may be for patients with traumatic or orthopedic pathologies who need partial weight bearing in their health care. The auditory feedback could warn the client if the load on the injured leg is too high to prevent damage during post-operative care. As the client's perception of the actual load is essential, easily available concurrent auditory feedback while walking or climbing stairs in a clinic could be decisive at this stage of rehabilitation.

This auditory biofeedback application could also help the client at home while performing activities of everyday life without the physical presence of a health professional. Moreover, a tool that provides feedback to the user while practicing independently can be crucial in order to actively involve a client in the rehabilitation process. According to self-determination theory, this may support a client's autonomy and thus foster motivation and adherence, and consequently improve the therapy outcome [27].

Elderly clients in particular have a higher risk of falls, which can impact their independence and in severe cases lead to death [30]. To assess the fall risk of a client, different assessments are used in a clinic or hospital to poll risk factors, e.g., history of falls, muscle weakness, poor balance, etc.[33]. A future application, in this case, might be a tool that observes the gait behavior of the client [5]. If the application registers deviations from the normal individual gait behavior and changes in the balance, it can send auditory feedback to alert the user. The client can then consciously check the situation. The recordings of these situations can help the client to discuss various solutions to reduce the risk of falls with health professionals. To prevent future falls, an exercise program for muscle strengthening and improving balance could be applied with the introduced tool including auditory biofeedback for personalized support at home and in rural communities.

In conclusion, we successfully demonstrated the feasibility of an auditory feedback system based on automated classification of functional gait disorders using an instrumented insole. An updated version of the insoles is by now classified as a medical product, which opens a large scope of potential applications and should be addressed in future research projects. The high potential of the implemented auditory feedback for preventive and supportive applications in physical therapy, such as supervised therapy settings and tele-rehabilitation, was highlighted by a semi-structured interview with two experts.

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