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Published in:
IEEE Transactions on Human-Machine Systems

DOI (link to publication from Publisher):
[10.1109/THMS.2021.3137013](https://doi.org/10.1109/THMS.2021.3137013)

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Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

[Link to publication from Aalborg University](#)

Citation for published version (APA):
Kantan, P. R., Spaich, E. G., & Dahl, S. (2022). A Technical Framework for Musical Biofeedback in Stroke Rehabilitation. *IEEE Transactions on Human-Machine Systems*, 52(2), 220-231.
<https://doi.org/10.1109/THMS.2021.3137013>

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A Technical Framework for Musical Biofeedback in Stroke Rehabilitation

Prithvi Kantan , Erika G. Spaich , and Sofia Dahl 

Abstract—In this article, we present a technical framework aimed at facilitating musical biofeedback research in poststroke movement rehabilitation. The framework comprises wireless wearable inertial sensors and software built with inexpensive and open-source tools. The software enables layered and adjustable music synthesis and has a generic movement–music mapping module. Using this, we designed digital musical interactions for balance, sit-to-stand, and gait training. Preliminary trials with subacute stroke patients indicated that the interactions were clinically feasible. Expert interviews with a focus group of clinicians were also conducted, where these interactions were deemed as meaningful and relevant to clinical protocols, with comprehensible feedback (albeit sometimes unpleasant or disturbing) for several patient types. We carried out system benchmarking, finding that the system has sufficiently short loop delays (~ 90 ms) and a healthy sensing range (> 9 m) and is computationally efficient (11.1% peak CPU usage on a quad-core processor). Future studies will focus on using this framework with patients to both develop the interactions further and measure their effects on motor learning, performance retention, and psychological factors to help gauge their true clinical potential.

Index Terms—Balance, biofeedback, gait, interactive sonification, music intervention, neurorehabilitation, stroke.

I. INTRODUCTION

STROKE survivors commonly suffer physical deficits that manifest as disturbances to balance and gait [1]. Advances in affordable computer power and portable motion-sensing technology [2] have led to an increasing role of technology in rehabilitation [3], for instance with biofeedback, where physiological or biomechanical information is made available to conscious experience to allow for greater self-awareness of bodily states, and modification where necessary [4]. *Biomechanical*

biofeedback [5] based on bodily kinematics or kinetics is the type of biofeedback most directly applicable to neurorehabilitation, specifically balance/mobility as well as lower limb activities and gait [6], [7]. Results based on studies with both healthy and impaired populations indicate the advantages of biofeedback in training compared to regular therapy protocols in improving postural sway [8], [9], weight shifting and reaction time [6], and sit-to-stand transfers [10] and gait kinematics [9], [11].

Auditory biofeedback (ABF) involves the real-time conversion of measured bodily information into a sonic representation. By definition, it can, thus, be seen as a specific case of interactive sonification [12], where data relations are rapidly converted into auditory relations [8], [13], [14]. The supplied auditory information on movement execution serves as continuous or discrete feedback, which can assist in movement error correction and/or accelerate motor learning [15]–[17] depending on the precise nature of the movement–sound mapping. Recent reviews highlight the potential of ABF in rehabilitation as well as the need for more and rigorous dysfunction- and task-specific studies, while also pointing out the present general lack of a framework for sonification in physiotherapy [18]. Although relevant technical frameworks have been developed (see, e.g., [19]), most prototypes are aesthetically limited to the most basic of feedback stimuli and fail to leverage the potential benefits of more complex sonic feedback media such as music. Our present study aims to address this by providing a technical framework for musical biofeedback (MBF) tailored for stroke patients, thereby facilitating the creation and evaluation of musical interaction paradigms that augment the rehabilitation process.

A. ABF in Movement Training

ABF has been applied to train postural control, with positive results [8], [13], [20], [21]. In a series of studies, Dozza and colleagues explored the use of multidimensional ABF using a system that sonified trunk accelerations/sway velocities *continuously* through frequency, level, and spatial balance of a stereo sound using nonlinear mappings. The feedback provided information similar to that given by the vestibular system [22], and the biofeedback improved balance overall, more so when other key sensory cues were unreliable or absent [13]. Direction specificity of audio biofeedback was found to reduce postural sway and increase the frequency of postural corrections in the direction of the biofeedback [20], [22]. Furthermore, the optimal mapping function for trunk sway to ABF was found to be sigmoid-shaped [21].

Manuscript received April 23, 2021; revised August 27, 2021 and October 29, 2021; accepted November 30, 2021. Date of publication January 10, 2022; date of current version March 14, 2022. This work was supported by NordForsk's Nordic University Hub "Nordic Sound and Music Computing Network" under Project 86892. This article was recommended by Associate Editor Xiaogang Hu. (Corresponding author: Prithvi Kantan.)

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Sekretariatet for Den Videnskabetiske Komité for Region Nordjylland.

This article has supplementary material provided by the authors and color versions of one or more figures available at <https://doi.org/10.1109/THMS.2021.3137013>.

Digital Object Identifier 10.1109/THMS.2021.3137013

Unlike the above continuous mapping paradigm, Costantini *et al.* [8] successfully tested a biofeedback system that projected trunk inclination onto discrete 2-D zones in the horizontal plane. Postural deviations triggered auditory warnings of proportional intensity using simple filtered and modulated noise. Though the authors only performed short-term evaluations with unimpaired subjects, they found significant reductions in postural sway in several conditions [8].

Engardt *et al.* [23] assessed the effects of ABF during training of *sit-to-stand* transfers in hemiparetic stroke patients, finding short-term improvements in body weight distribution between the paretic and nonparetic limb. Nicolai *et al.* [10] found significant and sustained improvements in posture and balance postintervention in patients with progressive supranuclear palsy. Patients received an auditory cue to stand up when the trunk flexion angle exceeded a threshold [10].

ABF has also shown positive effects in gait training [2], [7], [11]. For instance, sonifying ankle rollover patterns as a series of data-driven synthesizers was found to bring about significant differences in cadence and walking velocity among participants [14]. Torres *et al.* [24] introduced an *inertial measurement unit (IMU)*-based prototype and prescribed a number of movement-sound couplings, such as fixed movement thresholds to trigger discrete auditory feedback or modulate continuous auditory feedback [24].

B. Dynamic Trajectory Tracking

The above systems essentially provide *error-based* feedback [15], where the difference between a quantity and a constant “target” value is sonified over time. However, in the dynamic context of movement training, error feedback relative to a variable target may not be most ideal in terms of performance outcomes [16], [17], though extant research is inconclusive.

Rosati *et al.* [25] showed that error feedback did not improve performance over visual feedback alone, while a prescriptive auditory representation of the visualized target motion (*task-related* feedback) was more valuable. However, Boyer *et al.* [26] found that both these feedback types could reduce tracking error and increase movement energy in visuo-manual tracking. Parseihian *et al.* [16] conducted an audio-guided 2-D dynamic trajectory-tracking experiment based on the above research and found that prescriptive feedback resulted in superior tracking performance to error feedback. Due to the dynamic nature of the task, they found that pitch and other auditory dimensions that allow rapid comprehension and adjustments on the part of the user were most suitable [16].

The timing of task information may also be critical, specifically whether task information is provided simultaneously with user feedback or slightly in advance (allowing for user anticipation). An example of the former concurrently presented two sonifications corresponding to the task (reference) and user’s own performance, respectively, panned to opposite stereo locations, with the user’s goal being to make them sound identical [17]. Although the interaction was feasible and comprehensible, position- and timing-based user performance errors

(relative to target) were found to be significantly worse than with visual feedback. This is possibly due to auditory streaming [27], where the ongoing fusion and separation of the two signals may have made it difficult for the users to separate them for proper interpretation. On the other hand, Parseihian *et al.* [16] found that feedback based on *anticipated distance error* afforded far superior performance to merely instantaneous distance error.

Despite promise, ABF has failed to attain widespread practical adoption [28], [29], partly due to a lack of focus on aesthetics and naturalness in sonic interaction design [28] leading to poor user experience [30]. Most ABF systems reviewed here provide feedback through simple audio manipulations (e.g., pitch, loudness, brightness, and spatialization), which generate relatively simple feedback signals. These are known to cause auditory fatigue, annoyance, and dissatisfaction, making them less likely to be accepted by users [28]–[32]. Naturalness and clear causality in the iconic gesture-sound mapping of auditory displays have been found to contribute to their perceived usability [33]. For auditory displays, research has prescribed that auditory displays conform to some commonly shared aesthetic, e.g., based on internal schemata for embodied cognition [34].

C. Musical Biofeedback

The recent exploration of MBF [35]–[37] has attempted to address the aesthetics issues of ABF and leverage the universal emotional and sociocultural appeal of music. Music is a relatively complex signal due to its organization in time and frequency, possibly containing several instrumental and vocal elements to provide depth and variety to the feedback signal [36]. A general criticism leveled against such “aesthetic approaches” to sonification is that the interpretation of the underlying data is more difficult [29], [30] and in the case of music entails the learning of a new “sonic grammar” [38]. It has, however, been argued that there is a cultural or aesthetic baseline in popular music systems, which is accessible to untrained listeners and allows them to appreciate music with minimal cognitive overhead in the absence of formal training [38]. For instance, listeners are able to recognize music genres within a fraction of a second [39]. The psychological and therapeutic benefits of music are well known [40], and decades of research in the discipline of neurologic music therapy have established the direct therapeutic benefits of music across multiple dimensions in rehabilitation [41]. Several potential benefits of interactive music technology in healthcare have been named [35], [42], [43], related to motivation, engagement, and motor learning.

A typical MBF approach is to sonify desired movement behaviors as pleasant auditory states and undesired behaviors as unpleasant states, often simultaneously using musical rhythm to temporally organize motor timing [35]. The design space for possible *digital musical interactions* (DMIs) [44] is conceivably vast, and as such, MBF systems to date have ranged widely in scope and complexity, manipulating either prerecorded musical stimuli or real-time synthesized ones.

1) *Prerecorded Music*: Some MBF systems have utilized existing music waveforms, creating DMIs based on adding noise [45], filtering [32], [46], or adjusting audio quality [32], [47] to sonify physiological and biomechanical quantities. These interactions were found to be comprehensible by healthy and impaired populations and capable of positively altering motor behavior while reducing perceived exertion [46]. Others have sonified motor timing through music timing, such as the D-Jogger [48], which synchronizes pre-existing music to detected gait patterns using time stretching algorithms, thus providing a sense of rhythmic agency to the user [43].

2) *Synthesized Music*: Real-time synthesis approaches make it easy to exert control over a larger set of musical parameters and more easily craft more complex DMIs [49]. Sonification parameters used in these designs include musical pitch [50]–[52], tempo [36], brightness [51], mix balance [51], chord arpeggio characteristics [53], musical layer richness [54], synthetic tone additions [54], and percussive sample triggering [55]. In most cases, the systems only underwent preliminary evaluation such as brief usability tests with convenience-sampled healthy participants. However, at the very least, the results indicate that these MBF interactions are feasible, perceptible, and comprehensible, as well as potentially pleasurable experiences.

D. Appraisal of Earlier Work and Aim of the Present Work

In theory, combining music with the portability, versatility, and movement modification potential of ABF can enable powerful mediation of human behavior [43], since music can motivate, monitor, and modify human movement [35], and is as effective as simple sine sonification while reducing auditory fatigue [36]. However, many of the previously cited studies show that the feedback has modest clinical value. This could partly be due to the manner in which it is designed—the musical stimuli generated are usually *static and simplistic*, either monophonic instruments [50] or very basic ensembles [54], [56]. The synthesis of stimuli resembling professionally produced music is undoubtedly challenging. User experience can be hampered by barebones aesthetic designs [31], [53] that lack the consideration of user preferences [28], [57]. Biofeedback system customization for individual patients is an important feature [4], [18], and the extent to which extant systems allow it is unclear. Though some works mention the possibility of tailoring feedback to patients on the fly [24], [32], [58], MBF literature typically does not provide detailed system design specifications, and data mapping configurations appear *arbitrary and rigid* [59], difficult to alter in real time or retroactively tune [60] as part of user-centered approaches [43]. A platform that allows the generation of more complex music and user-configurable feedback could facilitate future investigation of MBF efficacy, providing a more accurate picture of its true clinical potential.

System design practices also present obstacles to the research community. The use of expensive proprietary/bespoke hardware and software [8], [10], [20], [21], [32], [61] makes these works difficult for other researchers to replicate, assess, and upgrade. Moreover, the use of visual programming environments in many

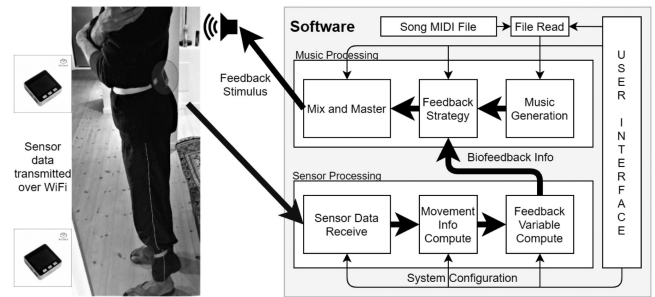


Fig. 1. High-level system schematic showing the organization of the hardware and software components of the framework, as well as the user wearing the wireless sensors.

studies [45], [48], [55], [56], [62], while excellent for preliminary testing, is computationally less efficient [37] and arguably harder to scale in complexity than low-level programming languages, although technical performance details are seldom reported in research. For example, most gait ABF systems claim to be “real-time,” but few report feedback loop delay values [58]. A notable exception is [19], but their low-latency embedded system had a simple synthesis engine that only generated two sine waves.

The aim of the present work was to address several of the stated shortcomings in current MBF systems and provide a more versatile framework to facilitate MBF research in balance and gait training. Through collaborations with patients and clinical stakeholders, we built a prototype aimed at contributing the following: 1) an inexpensive and replicable inertial motion capture system; 2) an architecture for synthesizing customizable and layered musical stimuli in real time; 3) a generic feedback mapping module to link computed movement parameters to MBF strategies; and 4) a set of DMIs for *balance*, *sit-to-stand*, and *gait* with clinical potential, realized through the mapping module. Our goal was to obtain a working system using exclusively low-cost and open-source development tools to ease replication. An important success criterion was that its technical performance needed to be practically viable in terms of wireless sensor range, biofeedback loop delay, and computational efficiency.

II. DESIGN AND IMPLEMENTATION

A. System Architecture

We opted for a *distributed* biofeedback structure [4] with wearable wireless inertial sensors and remote processing on a laptop. Sensor interfacing, music generation, and biofeedback configuration are controlled by a Windows application that produces a stereo audio signal, which is fed to the patient via headphones or loudspeakers, as shown in Fig. 1. *The source code of the system is available online and licensed under GNU GPL 3.0.*¹

The hardware sensing component consists of M5Stack Grey microcontrollers (€51 each) programmed in the Arduino IDE

¹[Online]. Available: <https://github.com/prithviKantanAAU/mbfFramework> V4

(free and open source). IMU data are transmitted to the software application as *Open Sound Control* (OSC) messages over WiFi-UDP. We wrote the software in C++ using the JUCE environment,² which is free of cost and has an efficient set of libraries for timer callbacks, OSC, MIDI, graphical elements, and file operations. For music synthesis and biofeedback, we implemented a FAUST³ script to generate a JUCE-compatible DSP object in C++ encapsulating the efficient audio DSP functionality of the FAUST language (also free and open source). The interface layout is organized into three tabs: sensor interfacing, music control, and biofeedback control. The software also enables real-time movement data visualization and time-series logging.

1) *Inertial Motion Capture and Communication*: Depending on the use case, there is either a single IMU sensor strapped to the patient's lower back or a pair of sensors strapped to the patient's ankles. Secure mounting is achieved using a silicone housing and velcro straps. The sensors connect to a secure WiFi network, which the laptop running the software is also connected to. After initializing the UDP ports through manual IP verification, the sensors transmit IMU data and battery status at 125 Hz to a predefined remote UDP port. The software periodically checks for new OSC messages received at each UDP port, thereby inferring whether the respective sensor is online. The sensor interface in the software allows assignment of the sensors to body parts (trunk or either leg), as well as a bias calibration option, where static offsets of the accelerometer and gyroscope axes are computed and compensated for postcalibration.

2) *Software Application Topology*: The software can be seen as a multi-instrument music synthesizer (FAUST DSP object) that generates performances from loaded MIDI data in real time (*sequenced music*). MBF is generated by manipulating the sequenced music using the movement data. The FAUST object has synthesizer controls related to instrument triggering, music mixing processors, and MBF strategies. This is handled by callback functions, as shown in Fig. 2. A single high-resolution timer orchestrates the music sequencing callback (at 1 kHz) and the MBF callback (at 100 Hz). The sensor transmission rate (125 Hz) exceeds the MBF callback frequency to compensate for UDP packet drops. UI updates (e.g., data visualization) occur independently at 30 Hz, and the real-time audio callback itself is handled by the FAUST object at a sampling rate of 48 kHz with a software buffer of 480 samples (adding 10 ms of software latency). The fact that the audio buffer duration and MBF callback interval are equal means that the effects of timing jitter are minimized.

B. Music Generation

The system generates an eight-track stereo instrumental ensemble containing melodic and percussive elements in a 4/4 time signature. These elements fulfill musical roles corresponding to percussion, melody, and harmony in a simplified pop music style, while allowing for real-time customization. Specifically,

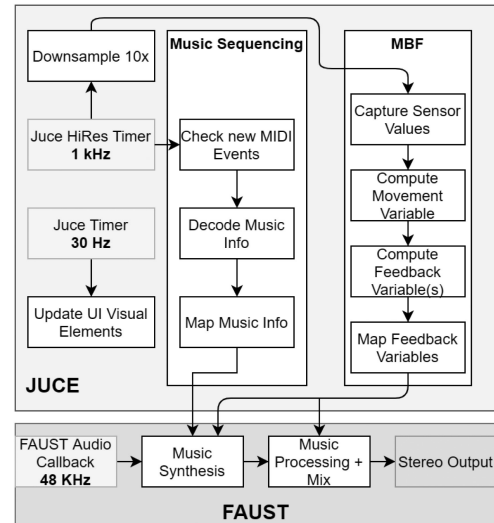


Fig. 2. High-level software schematic showing how the different functions (UI update, music sequencing, biofeedback computation, and music generation) are organized to run in timed callbacks at different frequencies.

the overall rhythmic groove and the instrument choices for each musical role/track can be individually modified. Other aspects of the music can also be varied on the fly, such as tempo, number of instruments, track balance, and mix processing parameters. The MIDI files used with the software are encoded in a custom Type-1 schema for efficiency. The sequencing system described next was developed entirely using JUCE functionality, whereas the synthesis combines FAUST DSP with preloaded drum samples.

1) *Sequencing*: MIDI messages for all tracks are decoded into pitch and velocity information to map to the appropriate FAUST synthesizer controls. For maximum flexibility, song information and rhythm/style information are stored in separate files. Song information related to melody, bass, and chord progressions is stored in MIDI *song files* that are loaded by the software user. Instrument choices, rhythmic information, and articulation for all tracks are encoded in *style files* that are dynamically prepopulated at software startup, facilitating the addition of new rhythms and styles to the software. At present, there are three styles: “Dance,” “Reggaeton,” and “Slow Rock.”

All MIDI information is stored as note matrices in program memory. During playback, the sequencing callback at 1 kHz (see middle branch of Fig. 2) increments the sequencer's elapsed MIDI ticks as per the configured tempo, checks MIDI timestamps in the note matrices for new events to be handled, and counts them. The event types are identified (note ON/OFF), and the event details (pitch/velocity) are preprocessed and mapped to the respective FAUST controls. The tempo slider controls playback rate by changing the tick increment per callback interval. Polyphonic tracks may have up to four voices (chords), and note frequencies are constrained to specific registers for pitched tracks to reduce sonic disparities among songs in different musical keys (refer to Section CS-A of the *supplementary material (SM)*, which will be referred to hereafter as **SM-CS-A**). Playback proceeds and the rhythmic pattern loops until the song file is complete.

²JUCE Framework—[Online]. Available: <https://juce.com/>

³FAUST Programming Language—[Online]. Available: <https://faust.grame.fr/>

2) *Synthesis*: Percussive instruments use prerendered samples, while melody instruments are synthesized using FAUST DSP. Each role can be reproduced in up to three distinct instrument textures, and combinations of these textures constitute a musical style preset. For example, the same percussive role can be played using a regular hi-hat, ride cymbal, or marimba sample. Synthesis is especially designed frequency modulation (FM) or subtractive synthesis, with basic physical models such as Karplus–Strong and formant-filtered vocal simulations (refer to **SM-CS-B**). Pitch parameters influence note frequencies of pitched tracks, while MIDI velocity influences volume and note articulation properties. Instruments have their own channel compressors and four-band fully parametric equalizers with predefined but modifiable settings. Envelope time constants, reverb, and echo time automatically adapt to the configured tempo. The tracks are summed and mastered using an equalizer and limiter, as in standard mixing workflows.

C. Movement Parameter Computation

The IMU signals received over UDP are read into buffers for further processing. They first undergo signal conditioning [60]—median filtering and smoothing using a sixth-order Butterworth low-pass filter. The system provides a list of computable movement parameters to choose for providing biofeedback on (e.g., orientation angles, jerk, etc.). As they are computed in a branching structure, it is straightforward to modularly add new parameters along with their metadata to the program structure. At present, the system computes the following parameters.

1) *Trunk Inclination Angles*: Angular displacement from the vertical in the [mediolateral (ML) and anteroposterior (AP)] directions is calculated from accelerometer and gyroscope readings using a complementary filter (algorithm described in [63]). A combined parameter is also provided, which converts these individual angles into a discrete 2-D representation, as done in [8].

2) *Mean-Squared Jerk*: As reviewed in [64], movements occurring in a continual fashion free of interruptions characterize most well-trained and healthy motor behavior and serve as a marker of poststroke motor recovery. We found that *mean-squared jerk* captures instantaneous intermittencies with sufficient speed and sensitivity for concurrent feedback on smoothness, as no segmentation or windowing is required. Accelerometer readings are first high-pass filtered to minimize the influence of the gravitational component, followed by first-order differentiation and squared norm calculation. Further filtering was not found to be necessary.

3) *Foot-Strike Detection*: This requires sensors attached to both ankles. Accelerometer signals receive high-pass filtering to filter followed by acceleration norm calculation. When the norm for a sensor exceeds a configurable threshold, it is registered as a step detection for the corresponding foot. To reduce false detections, a short *dead zone period* after each detection is assumed, during which threshold crossings are ignored. This dead zone is 80% of the beat interval of the music, so its absolute duration changes with tempo. We found this percentage to work best in our initial tests, although it may need to be

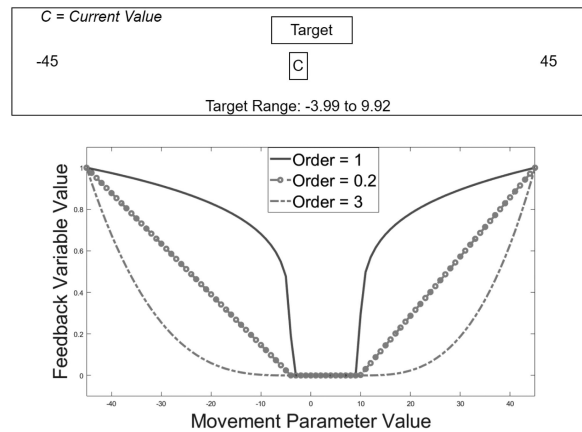


Fig. 3. Upper panel represents the real-time software visualization of the movement parameter relative to the configured target range. The lower graph shows how the FV value rises outside the target range for different gamma function orders.

made configurable in future versions. Moreover, once a step by one foot is detected, all threshold crossings on the same side are ignored until a threshold crossing (also known as step) by the opposite foot is detected. This detection forms the basis of 1) a gait-music periodicity compliance measure and 2) a step-synchronized impulsive trigger parameter for biofeedback.

D. Feedback Mapping Module

The chosen movement parameter is transformed to an intermediary *feedback variable (FV)* value that is finally mapped to a chosen MBF strategy control. Our framework allows any 1-D mapping combination between the movement parameters and the available MBF strategies (next subsection). In addition, it also allows a 2-D mapping of trunk ML and AP orientation to a pair of MBF strategies. Converting the movement parameter to the FV involves comparing its instantaneous value to a configurable *target range* and normalizing the error between 0 and 1 [28]. This is followed by a gamma scaling factor representing the mapping function shape [37] (see Fig. 3). Using a slider, this factor can be configured to scale linearly, logarithmically, or exponentially with the compliance error. This flexibility makes it possible to obtain an appropriate perceptual scaling of the MBF strategy in the context of a given training setting. A limitation is that certain function shapes are not achievable in this way (e.g., sigmoid or logit functions).

As shown, an FV value of 1 indicates maximum MBF intensity and *vice versa*. It is mapped to the chosen MBF strategy control of the FAUST object, which accordingly manipulates the music generation process. The software provides real-time 1-D and 2-D visualizations of movement parameter values, mainly to assist the therapist in tailoring the system behavior to individual patients. These are represented in Fig. 3 (upper portion) and Fig. 4. Note that these visualizations are not meant to be presented to the patients (except during dynamic balance training) and are only meant to help the therapist monitor patient performance.



Fig. 4. 2-D plane visualization used during balance training, providing real-time information on the progress of the target trajectory as well as the 2-D inclination angles of the patient.

E. Musical Sonification Strategies

The FV manipulates FAUST DSP controls corresponding to the selected MBF strategy, which may be continuous or discrete, provide positive or negative reinforcement, and be controlled by any movement parameter. While this appears to be a simple one-to-one mapping to a single auditory dimension, most of our MBFs internally contain one-to-many mappings (i.e., multiple audio signal parameters affected simultaneously by the FV) so as to create a unified effect that is understood as a single conceptual Gestalt [65]. We here give an overview of the strategies implemented, as well as links to A/V demos. **SM-V1** demonstrates some strategies operating in the 1-D framework without context, whereas **SM-V2-(A-D)** show them in the context of training use cases (further elaborated in the next section). Code snippets are in **SM-CS-C**.

a) Continuous Strategies:

- 1) *Sound degradation*: Principally, these strategies bring about a continuously scaled degradation of the music quality.
- 1) *Ring modulation*: This simultaneously maps the FV to the modulation depth and bandwidth of a ring modulator applied to the melody and harmony instruments of the music, creating sidebands manifesting as salient dissonance and distortion (refer to **SM-V2-A-c**).
- 2) *Dissonance*: This i) offsets chord note fundamental frequencies to dissonant intervals and ii) applies tempo-dependent FM to the melody, creating a pitch-wobbling effect that renders it unrecognizable as the modulation depth increases (refer to **SM-V1** and **SM-V2-A-b**).
- 3) *Melody pitch*: This operates bidirectionally and is an exception to our previously established unipolar 0–1 FV convention. Here, the nominal value is 0.5, while 0 and 1 represent the directional extremes. A multiplicative factor is applied to the fundamental frequency of the melody,

equaling 1 when the FV value is 0.5, 10 when the FV is 1, and 0.1 when it is 0. This leads to very pronounced pitch excursions when the FV increases or decreases from 0.5 (refer to **SM-V2-B**).

- 4) *Wah–wah*: This uses the FV value to modulate the depth of a wah–wah effect, which is not strictly a sound degradation, but potentially annoying with prolonged listening (refer to **SM-V1**).

b) *Interruption*: These strategies mute the melody/harmony instruments, replacing them with unpleasant waveforms like sawtooth waves or filtered noise. Simultaneously, percussion timing is distorted using modulated delays (refer to **SM-V1** and **SM-V2-C-a**).

2) Discrete Strategies:

- 1) *Cartoon strategy*: This feedback strategy replaces a) the drums with simple bandpass filtered percussive sounds and b) the melody instruments with detuned sawtooth wave versions of themselves as the FV crosses a threshold. Hence, compliance is rewarded with an in-tune and normal-sounding music ensemble (refer to **SM-V2-A-d**).
- 2) *Ambulance strategy*: This is an interruption strategy; an ambulance siren is simulated using a frequency-modulated triangle wave, and feedback intensity is increased by increasing the modulation frequency in discrete steps, with the goal of making the effect more intense as the FV increases (refer to **SM-V1** and **SM-V2-A-a**). The siren is, thus, not “musical” by itself, but its absence (also known as uninterrupted music) indicates compliance with the target range.
- 3) *Instrumentation strategy*: Instruments from the ensemble are muted one by one as the FV increases. The patient receives a full multitrack ensemble when the FV (also known as compliance error) is zero (refer to **SM-V1**).
- 4) *Triggered impulsive entities*: These strategies trigger transient sounds at specific FV values.
 - i) *Bell*: This strategy triggers the physical model of a church bell (refer to **SM-V1** and **SM-V2-C-b**).
 - ii) *Bass and snare drum triggering*: This mutes the bass drum and snare drum from the sequenced music and allows them to be manually triggered by the patient (e.g., during walking) (refer to **SM-V2-D-b**).

F. Movement–Music Interactions

1) *Static Balance*: The principle is to reward the maintenance of a static target trunk orientation (upright or inclined, sitting or standing) with pleasant music and provide negative MBF proportional to deviations from this target. The ML and AP angles can be sonified in a 2-D discrete combination, where angular trunk tilt from the vertical is projected onto the horizontal plane formed by the ML and AP axes and allocated to one of six discrete feedback zones. These zones are concentric circular or elliptical ring shapes centered around a pair of *target 2-D orientation* coordinates [8]. There are two rectangular zones to the extreme left and right, where directional feedback in the form of panning/spatialization can be provided. The target can be offset to a nonupright position, and its zone size can be changed

to accommodate differently able patients. Continuous sound degradation or discrete warning strategies may be used here, and the number of distinct-sounding feedback levels depends on strategy and mapping function choice (refer to **SM-V2-A-a,b,c,d**).

2) *Dynamic Balance*: Trunk training typically involves core stability exercises based on trunk flexion, extension, weight shift, and reaching movements [66] and has more recently been augmented by visual posturography-based paradigms such as the Balance Master,⁴ which provides visual feedback. This DMI is a musical augmentation of this paradigm. Here, the 2-D target moves in a horizontal plane trajectory that the patient must match, in a configurable linear, diagonal, circular, square, or rhombic shape. The patient is informed about the moving target through the real-time visual interface, as shown in Fig. 4, and attempt to match it.

In addition to the visual cues, the frequency and phase of the trajectory progress are music-synched so that rhythmic cues thereof can assist movement planning, and the trajectory frequency can be adjusted to a submultiple of the music tempo to suit the patient's speed. 2-D anticipated distance error (as in [16]) is fed back through an MBF strategy combination such as left-right spatialization for ML and melody pitch for AP feedback (refer to **SM-V2-B-a**). A sum of sigmoid functions is used to map directional feedback for maximum perceptual salience.

3) *Sit-to-Stand*:

- 1) *Jerk-based*: This DMI rewards smooth sit-to-stand transitions with pleasant music, providing negative MBF to detected movement intermittencies by introducing salient disturbances in the music based on the mean-squared jerk. An example use case is that of sitting down on a chair, where many stroke patients tend to drop down onto the chair rather than smoothly lowering their bodies. Providing jerk-based MBF here can help focus their attention on this phase of the movement and encourage them to avoid such sitting motions. On doing so, they receive positive reinforcement in the form of normal music. We found that the continuous interruption strategies are most suitable here due to their perceptual salience (refer to **SM-V2-C-a**).
- 2) *Trunk flexion-based cues*: A sit/stand action cue is provided based on *trunk flexion angle*. We augmented the principle musically here by using the *bell* or *wah-wah* MBF strategy to provide sit/stand action cues when forward leaning angle thresholds are exceeded (refer to **SM-V2-C-b**).
- 4) *Gait*: The purpose of these DMIs is to augment rhythmic auditory stimulation training [40], [41] by providing immediate feedback on motor synchronization with the music. The two DMIs focus on step *duration* and *phase*, respectively.

- a) *Period matching*: The system keeps track of time elapsed since the last detected step and behaves as follows for subsequent steps.

- 1) If no new step is registered by the time it should have arrived (as per the musical beat interval), negative feedback is provided until the new step is detected, and the time counter is reset.
- 2) If the new step arrives too early compared to the beat interval, the time counter is reset, and negative feedback plays for a duration equaling the step-duration/beat-period mismatch.

A timing tolerance as a percentage of the beat interval is configurable in the interface, and no negative feedback is applied to step durations falling within this tolerance. We found interruption strategies to be most perceptually salient for this DMI, wherein good period matching is rewarded with uninterrupted music and *vice versa* (refer to **SM-V2-D-a**).

- b) *Phase matching*: This is inspired by [55] and [56]. Here, percussive musical events are triggered by footfalls (drum trigger strategy), and the training goal is to synchronize these events with the remaining instruments. Here, the bass drum and snare drum triggering strategy is controlled by the detected foot strikes. By walking in time, the patient is, thus, rewarded with a well-synchronized ensemble (refer to **SM-V2-D-b**).

III. EVALUATION

We performed formative and summative evaluations: Following our second development cycle, we conducted a preliminary usability study with stroke patients to test the DMIs in a clinical setting, albeit without a rigid protocol (see Section III-A). After the final development stage, we carried out a focus group interviews with experts to assess the clinical potential of the DMIs (see Section III-B) and system benchmarking to test important technical performance parameters of the framework (see Section III-C).

A. DMI Testing With Subacute Stroke Patients

Six subacute stroke patients (four men and two women) with predominantly one-sided weakness admitted at Neuroenhed Nord, Frederikshavn, Denmark, volunteered to participate in this DMI usability test. Our inclusion criteria for each DMI were that the patients were hemiparetic and in the subacute phase, and undergoing routine physical therapy to train the function corresponding to that DMI (i.e., balance, sit-to-stand, or gait). As per the North Denmark Region Committee on Health Research Ethics, the study did not require an approval from the research ethics system; cf. the Danish Act on Research Ethics Review of Health Research Projects (inquiry date August 8, 2019).

Only the *static balance*, *jerk-based sit-to-stand*, and *gait* DMIs had been developed at that point. A subset of the DMIs was allocated to each patient based on their therapy needs, and we adjusted the mapping parameters to match the patients' individual physical abilities. We equipped the patients with the sensing hardware, and a physiotherapist conducted some routine training exercises with MBF playing through a monophonic loudspeaker placed in the room. We found that the movement measurement mechanisms largely worked as intended, and the main findings are summarized as follows.

⁴[Online]. Available: <https://www.cephalon.eu/products/balance/balance-master/>

- 1) *Static balance (one patient)*: The patient was able to perceive and understand the timbre degradation MBF strategies and appeared to exhibit greater levels of arousal due to the music. However, the physiotherapist estimated that the MBF needed to be more perceptually salient to accommodate patients with more severe cognitive impairments.
- 2) *Sit-to-stand (four patients)*: Overall, patients were able to clearly hear and understand the MBF and reported that they enjoyed the activity as well as the way in which they could hear their movements. On a few occasions, the jerk MBF was triggered even when patients felt their movements were smooth, which puzzled them.
- 3) *Gait (four patients)*: All patients were able to follow and match the musical rhythm, except one who initially had difficulties hearing the beat. This required the percussion instruments to be amplified in the music mix. All patients were able to understand both DMIs and clearly hear the feedback, although they reportedly enjoyed the phase-matching DMI more, due to the direct musical agency and control it gave them. Most patients had periods of good and poor synchronization depending on concentration and distance from the loudspeaker and sometimes needed to be verbally cued back into rhythm. Two patients increased their gait cadence significantly as the training progressed, which required the music tempo to be manually adjusted to match them. One patient had noticeable step time asymmetry, which made period matching difficult.

B. Focus Group Interviews—Experts

To assess the clinical potential of the DMIs, we evaluated them via structured interviews with a focus group consisting of five physiotherapists and two music therapists. The interviews were conducted online after our third development cycle. Video demos of the DMIs were presented of the first author interacting with the system (refer to **SM-FG1**), followed by a fixed set of questions exploring both the clinician's and indirectly the patient's perspective.⁵ The interviews were transcribed and coded by an inductive approach into a hierarchical coding scheme (refer to **SM-FG2**). A short summary of key takeaways is given here, and the full data summary is given in **SM-FG3**.

1) *Clinical Utility*: The experts were able to provide insight on stroke patient subgroups that can potentially benefit from each of the DMIs. Three expressed that the *static balance* DMI could be used across acute/moderate patient groups, while the *dynamic balance*, *sit-to-stand*, and *gait* DMIs would need to target progressively less severe patients (refer to **SM-FG3**). Two stated that for the *gait* DMIs, patient inclusion would depend not only on impairment severity, but also on the location of the infarction/bleed (e.g., cerebellar or lower brainstem strokes are better candidates). Certain exclusion criteria were also outlined; four experts felt that patients with severe auditory perceptual difficulties and cognitive impairments would not be able to use the feedback, and one added that suboptimal spatial abilities

would preclude the use of the *dynamic balance* DMI. Two felt that patients lacking rhythm-finding abilities would be unable to benefit from the *gait* DMIs.

The interviews also probed whether the sensors and chosen movement parameters could capture the movement information of clinical interest during rehabilitation. For all five DMIs, at least two experts explicitly stated that this was so (refer to **SM-FG3**) on the basis of the demo videos. One did state that the system did not seem to distinguish between jerky movements and merely rapid movements. However, two experts said that the *jerk* and *gait* DMIs provided therapists with additional valuable information not available visually (e.g., movement intermittencies, step rhythmicity) (refer to **SM-FG3**). They did not feel that this was so for the *static* and *dynamic balance* DMIs, although one did state that the spatial information provided by the MBF was potentially more “exact” due to the precision of the sensor compared to the human eye.

2) *Clinical Usability*: Three experts explicitly stated that the five individual DMIs were compatible with and could easily be integrated into the respective physiotherapy protocols, particularly goal-oriented training (refer to **SM-FG3**). Moreover, two also said that they could aid patient autonomy outside the hospital setting. For instance, the *static balance* DMI could be used at home (e.g., while watching TV or sitting on a chair) and could, according to one expert, be advantageous over existing visual biofeedback systems in terms of cost and portability. Two experts also said that the *dynamic balance* DMI could be used to create “fun training” scenarios. On the other hand, two experts were skeptical about the idea of directly converting jerk information into feedback, especially in the case of patients whose muscle weakness makes jerky movements unavoidable. Finally, some adaptations of the DMIs were suggested for other types of training (refer to **SM-FG3**), such as using jerk feedback to treat writing tremors (two experts) and the *gait (phase matching)* DMI for pregait training (one expert).

Two experts highlighted practical considerations, most importantly the matter of patient safety in DMIs involving full-body movement (sit-to-stand, gait) and stressed that it was important for therapists to be able to use the system in a hands-free manner. For the *gait* DMIs, one expert suggested that it may make sense to use bodyweight-supported systems along with treadmills, but another mentioned practical problems with treadmill training due to the complexity of setting treadmill speeds for different patient types. There were no concerns raised regarding the sensing hardware, but one expert did mention that using velcro straps could damage clothing and should be replaced by elastic straps, and that hygiene measures needed to be taken if the same hardware was to be shared by multiple patients. For the *dynamic balance* DMI, there was no consensus on the necessity of the visual feedback, with experts divided in terms of how important it was to the task. One expert brought up the issue of setup time, saying it would help if the system configuration were possible on a mobile device, and if patient-specific settings could be saved for future recall.

3) *Patient Usability*: The experts also assessed the synthesized music and DMI-specific MBF strategies from the perspective of a stroke patient, based on their experience. Related

⁵See expert interview info sheet: [Online]. Available: https://docs.google.com/document/d/1d6xWIIaIwsD-lf-NhUBszqJzxnVC9M_yw1frMFPY4m0/edit?usp=sharing

to the music, two experts acknowledged that there was a high degree of subjectivity based on patient preferences and past music consumption (refer to **SM-FG3**), but that they appreciated the stylistic variety provided by the system. One stated that down-tempo music might be suited to the *static balance* DMI (to avoid inducing movement) and *gait* DMIs for slow-walking patients.

Concerning the MBF itself, there was good agreement that it was provided in a timely manner, and that the patient-specific adjustments were sufficiently flexible (two to three experts stated this explicitly per DMI). Experts also commented on the nature of individual MBF strategies in the context of each DMI. For *static balance*, three experts favored the *ambulance* strategy, saying it was easily perceptible without being overly annoying. The *dissonance* and *ring modulation* strategies were described as clear but very annoying by one expert, while the *cartoon* strategy was found less annoying but perceptually blurry. In the *dynamic balance* DMI context, three experts felt that the optimal MBF strategy would depend on the patient's perceptual abilities, and hence, the ability to choose was important. Two experts stated that the *instrumentation* strategy was not perceptually salient. However, for the *jerk feedback*, three experts found the interruption strategies easy to perceive and intuitive (refer to **SM-FG3**). In the *sit-to-stand* (trunk flexion-based cues) DMI, two participants found the bell strategy to be too soft and suggested that the volume of the bell be made adjustable. Experts were also divided on the use of the wah-wah effect as a movement cue. As for *gait*, three experts preferred the *phase matching* DMI as they felt it provided direct positive reinforcement as compared to the *period matching* DMI, which two experts found excessively annoying. One expert did express that the difference between the left and right foot drum sounds in the *phase matching* DMI could be more pronounced.

C. System Benchmarking

System benchmarking was carried out on a Dell Inspiron 15 7000 Windows laptop with a 1.8-GHz i7 processor and 16-GB RAM. A USB-connected Focusrite 18i8 audio interface was used for audio output, which was auditioned through a pair of Beyerdynamic DT-880 Pro headphones.

1) *Biofeedback Loop Delay*: This was measured by comparing onset timestamps between *system input* and *output (sound)* during the *gait (phase matching)* DMI, as the impulsive nature of foot strikes made it a suitable candidate for temporal measurement. We calculated loop delay by comparing simultaneously recorded audio files corresponding to system input (footstep sounds recorded using a mobile phone recorder) and system output sound (triggered bass drum and snare drum captured by WASAPI Windows audio driver). A sine burst was first recorded by both as a temporal alignment reference, and 19 steps were then taken in a quiet room. The two audio recordings were captured, and event timestamps were extracted using the transient detection functionality in REAPER, which detects physical onsets in audio with high temporal accuracy (under 1 ms for impulsive sounds). Corresponding foot strike and drum

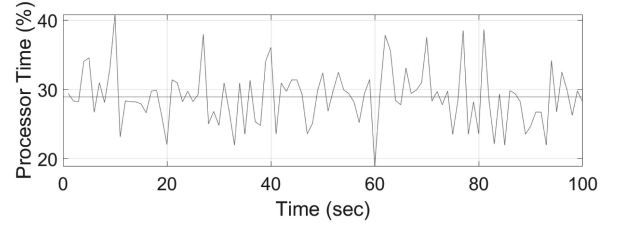


Fig. 5. % processor time plotted against time (second) during the final test. The horizontal line denotes the mean % processor time.

TABLE I
COMPUTATIONAL PERFORMANCE

Parameter	Test Duration	Value
% Processor Time Mean (STD)	100 s	28.91 (4.09)
% Peak CPU Usage		11.1
Memory		157.1 MB

transient timestamps were subtracted and aggregated to yield the *mean (STD) loop delay value of 93 (48) ms*.

2) *Computational Performance*: We measured this in the form of *% processor time*, i.e., as the percentage of total time that is spent by the CPU on executing the software application code. This time is expressed relative to the total available processing capability, i.e., each core operating at 100% capacity \times number of cores (4 on test machine), in other words a theoretical maximum capacity of 400%. In practice, the available processor headroom is lower as JUCE by default does not multithread audio processing tasks, meaning that the application practically uses two cores at the maximum for audio, GUI, and other internal tasks. Hence, a *peak processor time value less than 100% guarantees that there are no bottlenecks at any one core at any time*. We used the Windows Performance Monitor to record logs of processor time at a resolution of 1 s, which we then analyzed in MATLAB. The CPU usage % of the software in the Windows Task Manager was also monitored.

We compared the different music styles at the tempo extremes to find the most demanding scenario, which turned out to be the “Slow Rock” style at 60 beats/min. This style was used in the final CPU stress test, where music playback was combined with the most complex DMI (dynamic balance training with 2-D feedback) with logging and visualization enabled. % processor time was logged and is shown in Fig. 5, along with the results in Table I.

3) *Sensor Range*: We assessed the indoor sensor range in terms of the percentage of MBF callbacks that detected new OSC messages in a short time frame under different conditions. In our experiment, a single-sensor transmitted OSC packets to the laptop, which was set up in the corner of a large furnished room. Results are in Table II.

IV. CONCLUSION

In this article, we presented an MBF framework for post-stroke movement rehabilitation codeveloped with stakeholders and addressing several shortcomings of existing systems by

TABLE II
SENSOR RANGE

<i>Distance Condition</i>	<i>Test Duration</i>	<i>% Callbacks w/ UDP Packet Recd.</i>
3 m (Direct Line-of-Sight)	20 s	96.35
7 m (Direct Line-of-Sight)		96.10
9 m (Around Wall Corner)		82.50

integrating theories of biofeedback system design [4], auditory guidance [28], music therapy [41], MBF [35], and interactive sonification [37], [60]. Our generic mapping module enabled the creation of multiple DMIs catering to conventional protocols for balance and gait training within a single real-time architecture. Here, we discuss the present contribution and our evaluation outcomes.

The sensing apparatus (M5Stack-Grey) we used for motion capture is light, portable, inexpensive, and easily available. Moreover, its wireless functionality is easily replicable using our code and was shown to have sufficient range for indoor use during our evaluation. Our interviewees' positive opinions of its movement capture capabilities and extra informative potential point to the robustness of the hardware and movement parameter computation. However, the inability to disambiguate jerky and rapid movements must be addressed in future versions. The mounting apparatus can be modified to use elastic straps instead of velcro, in addition to ensuring that the material can easily be sterilized between sessions.

Using free software environments (JUICE and FAUST), we were able to create a versatile architecture for layered, yet computationally efficient real-time music synthesis. Its flexibility can help tailor stimuli to patients, both in terms of therapy goals (e.g., matching music tempo gait cadence, amplifying rhythm, or melody) and individual taste (through musical style, groove, and song MIDI). This was done in an effort to address the aesthetics problem [28], [29] and accommodate user preferences [57]. However, there is still significant upgrade potential. From the comments made by the clinicians (primarily not music experts), the architecture has limitations. This could be because the synthesis methods are relatively simple, and the sequencing process is deterministic and predictable with limited temporal variability. Even taking into account subjectivity in music preferences, the system generally produces a computerized-sounding output. In addition, MIDI file encoding is not trivial and requires musical knowledge as well as technical skills. Future versions could integrate computational rules [49] for expressive music performance, as well as a MIDI library of known songs.

Our generic mapping module enables a large number of movement parameters and MBF strategies to be linked to one another and adjusted in terms of perceptual scaling [60]. The modularity of its operation allows these parameters and strategies to be combined and customized, allowing rapid testing of a large number of possible MBF paradigms. We believe that this can facilitate the addressal of extant MBF design issues in future research, simply due to the ability to test various MBF configurations. Although our feedback dimensionality [60] is low (1-D or 2-D), we argue that it suffices for the target group, a large proportion

of which suffers from cognitive impairments [1]. This is likely to hinder them in understanding a larger number of concurrent feedback channels. The generic nature of the mapping module makes it possible to simply “plug in” new movement parameters and MBF strategies and cross-map them in real time for comparison in a clinical setting. For example, force plates can be used for balance training within the same OSC transmission framework, and new DMIs related to poststroke footdrop can be designed, wherein the IMUs are placed on the foot instead of the shank. Another possible upgrade is to allow the choice of more complex mapping function shapes.

As indicated by the focus group interviews, our DMIs have the potential to be applied to patients at various stages of recovery, ranging from acute to subacute. During clinical testing, it is important that DMIs are allocated and configured in tight accordance with the pathologies and needs of patients, identifying the presence of exclusion criteria such as perceptual, cognitive, or rhythm-finding difficulties, as well as a general disinterest in music and/or technology [43].

It is encouraging that the experts deemed our DMIs compatible with existing rehabilitation protocols, capable of augmenting them and even adaptable to other training scenarios. However, we acknowledge that there was a risk of bias in our question framing and data collection methods. In future studies, we will place greater focus on posing more neutral-connotation, open-ended, and scale-based questions in robust blinded setups. Moreover, the technical framework has not undergone any empirical evaluation in a rehabilitative setting, making it difficult to gauge the DMIs' true clinical utility [18], [67]. Therefore, the interview outcomes pertaining to the DMIs and MBF strategies must be interpreted with caution. For example, it is unclear whether patients will be able to translate jerk-based feedback into a meaningful and sustainable change in biomechanics. This uncertainty is compounded by the large variability exhibited by stroke patients, both physical and cognitive. For instance, the second gait-based DMI converts foot strikes into drum hits and relies on the ability of the patient to discern beat discrepancies and correct them—a skill that not all patients will have. Perhaps, it may be necessary to provide more dynamic information to patients to help them adjust their steps for more rhythmic gait. For instance, the *timbre* of the triggered drums could be manipulated differently depending on whether the detected step is early, late or within tolerable limits based on the beat interval.

There appeared to be a connection between the experts' estimations of perceptual salience and unpleasantness of the MBF strategies. Specifically, strategies that were very perceptually salient also tended to be judged as very unpleasant, and *vice versa*. Although the biofeedback relies on a clear contrast between pleasant and unpleasant musical states [35], further tests with patients must further investigate this tradeoff between feedback salience and pleasantness [60] to inform the MBF design philosophy. As reviewed in [58], positive feedback may generally be more conducive to long-term motor learning than negative feedback as it promotes motivation and invokes dopamine prediction error mechanisms, as opposed to simply eliciting the attentive processing of movement errors. This can be part of why multiple experts preferred the *phase matching*

gait DMI to the *period matching* one. Perceived unpleasantness is also likely to vary among patients [28], but a better understanding of this topic is very important in order to leverage the potential benefits of MBF and avoid auditory fatigue among patients. Several of our DMIs and MBF strategies primarily provide error-based negative feedback, which may neither be ideal for sustained use with the target group nor have significant benefits over traditional paradigms.

Our preliminary usability study and focus group interviews yielded some insight related to the DMIs. The tests with patients showed that several DMIs were understandable and practically applicable, although the sample was small and comprised subacute patients. It is encouraging that multiple experts deemed our DMIs to be sufficiently adjustable for individual patient tailoring, as this is critical to the usability of the framework [43]. The experts' agreement that the biofeedback was provided in a timely manner is in line with the measured biofeedback loop delay, which was less than the human auditory reaction time [4], [58] and within the limit of perceived simultaneity [68].

Our future studies will include rigorous usability studies and clinical trials, where we systematically compare MBF strategies and assess ratings of enjoyment, arousal, and perceived agency. We will also focus on adding DMIs and MBF strategies to the framework, aimed at providing positive feedback that reinforces task-intrinsic perceptual information critical to motor learning (e.g., proprioception, and/or using embodied schemata) [34], [59], [69]. Additionally, we shall focus on DMIs that provide feedback to enhance compensatory mechanisms and strategies to overcome loss of motor function, as opposed to only sonifying deviations from "desirable" performance [67]. Ultimately, it is the modularity and flexibility of our framework that will facilitate the addressal of DMI design issues, as well as the clinical assessment of DMIs and MBF strategies. We believe that our framework provides a means for the research community to better understand the potential benefits of using MBF in stroke rehabilitation.

ACKNOWLEDGMENT

The authors would like to thank Helle Rovsing Møller Jørgensen and the participating patients and therapists. The authors would also like to thank the reviewers for helpful comments on this manuscript. The author Prithvi Kantan was main responsible for system development and manuscript writing. The authors Erika G. Spaich and Sofia Dahl supervised the M.Sc. project [63] and assisted in writing. All authors approved the final manuscript.

REFERENCES

- [1] R. Sacco *et al.*, "An updated definition of stroke for the 21st century: A statement for healthcare professionals from the American Heart Association/American Stroke Association," *Stroke, J. Cereb. Circulation*, vol. 44, pp. 2064–2089, May 2013.
- [2] C. Ma, D. Wong, G. W. Lam, A. Wan, and W. Lee, "Balance improvement effects of biofeedback systems with state-of-the-art wearable sensors: A systematic review," *Sensors*, vol. 16, Mar. 2016, Art. no. 434.
- [3] F. Horak, L. King, and M. Mancini, "Role of body-worn movement monitor technology for balance and gait rehabilitation," *Phys. Ther.*, vol. 95, pp. 461–470, Dec. 2015.
- [4] A. Kos and A. Umek, *Biomechanical Biofeedback*. New York, NY, USA: Springer, 2018.
- [5] O. Giggins, U. M. Persson, and B. Caulfield, "Biofeedback in rehabilitation," *J. Neuroeng. Rehabil.*, vol. 10, 2013, Art. no. 60.
- [6] A. Zijlstra, M. Mancini, L. Chiari, and W. Zijlstra, "Biofeedback for training balance and mobility tasks in older populations: A systematic review," *J. Neuroeng. Rehabil.*, vol. 7, 2010, Art. no. 58.
- [7] J. J. Tate and C. E. Milner, "Real-time kinematic, temporospatial, and kinetic biofeedback during gait retraining in patients: A systematic review," *Phys. Ther.*, vol. 90, no. 8, pp. 1123–1134, Aug. 2010.
- [8] G. Costantini *et al.*, "Towards the enhancement of body standing balance recovery by means of a wireless audio-biofeedback system," *Med. Eng. Phys.*, vol. 54, pp. 74–81, 2018.
- [9] K. Gordt, T. Gerhardy, B. Najafi, and M. Schwenk, "Effects of wearable sensor-based balance and gait training on balance, gait, and functional performance in healthy and patient populations: A systematic review and meta-analysis of randomized controlled trials," *Gerontology*, vol. 64, no. 1, pp. 74–89, 2018.
- [10] S. Nicolai *et al.*, "Improvement of balance after audio-biofeedback: A 6-week intervention study in patients with progressive supranuclear palsy," *Zeitschrift für Gerontologie und Geriatrie*, vol. 43, pp. 224–228, 2010.
- [11] R. Stanton, L. Ada, C. M. Dean, and E. Preston, "Biofeedback improves performance in lower limb activities more than usual therapy in people following stroke: A systematic review," *J. Physiotherapy*, vol. 63, no. 1, pp. 11–16, 2017.
- [12] A. Hunt and T. Hermann, "Interactive sonification," in *Sonification Handbook*, T. Hermann, A. Hunt, and J. G. Neuhoff, Eds. Berlin, Germany: Logos Verlag, 2011.
- [13] L. Chiari, M. Dozza, A. Cappello, F. Horak, V. Macellari, and D. Giansanti, "Audio-biofeedback for balance improvement: An accelerometry-based system," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 12, pp. 2108–2111, Dec. 2005.
- [14] B. Horsak *et al.*, "SONIGait: A wireless instrumented insole device for real-time sonification of gait," *J. Multimodal User Interfaces*, vol. 10, no. 3, pp. 195–206, 2016.
- [15] F. Bevilacqua *et al.*, "Sensori-motor learning with movement sonification: Perspectives from recent interdisciplinary studies," *Front. Neurosci.*, vol. 10, 2016, Art. no. 385.
- [16] G. Parsehian, M. Aramaki, S. Ystad, and R. Kronland-Martinet, "Sonification strategies for dynamic guidance tasks: Example with a driving game," in *Proc. 13th Int. Symp. Comput. Music Multidisciplinary Res.*, 2017, pp. 283–294.
- [17] M. Matsubara, H. Kadone, M. Iguchi, H. Terasawa, and K. Suzuki, "The effectiveness of auditory biofeedback on a tracking task for ankle joint movements in rehabilitation," in *Proc. 4th Interact. Sonification, Workshop*, 2013, pp. 1–6.
- [18] J. Guerra, L. Smith, D. Vicinanza, B. Stubbs, N. Veronese, and G. Williams, "The use of sonification for physiotherapy in human movement tasks: A scoping review," *Sci. Sports*, vol. 35, no. 3, pp. 119–129, 2020.
- [19] H.-P. Brückner, M. Wielage, and H. Blume, "Intuitive and interactive movement sonification on a heterogeneous RISC/DSP platform," in *Proc. 18th Int. Conf. Auditory Display*, Atlanta, GA, USA, 2012, pp. 75–82.
- [20] M. Dozza, "Biofeedback systems for human postural control," Ph.D. dissertation, Dept. Electronics, Comput. Sc., Syst., Alma Mater Studiorum, Univ. di Bologna, Bologna, Italy, Apr. 2007.
- [21] M. Dozza, L. Chiari, F. Hlavacka, A. Cappello, and F. Horak, "Effects of linear versus sigmoid coding of visual or audio biofeedback for the control of upright stance," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 4, pp. 505–512, Dec. 2006.
- [22] M. Dozza, L. Chiari, R. J. Peterka, C. Wall, and F. B. Horak, "What is the most effective type of audio-biofeedback for postural motor learning?," *Gait Posture*, vol. 34, no. 3, pp. 313–319, 2011.
- [23] M. Engardt, T. Ribbe, and E. Olsson, "Vertical ground reaction force feedback to enhance stroke patients' symmetrical body-weight distribution while rising/sitting down," *Scand. J. Rehabil. Med.*, vol. 25, no. 1, pp. 41–48, Mar. 1993.
- [24] A. V. Torres, V. Kluckner, and K. Franinovic, "Development of a sonification method to enhance gait rehabilitation," in *Proc. ISON 4th Interact. Sonification Workshop*, 2013, pp. 37–43.
- [25] G. Rosati, F. Oscari, S. Spagnol, F. Avanzini, and S. Masiero, "Effect of task-related continuous auditory feedback during learning of tracking motion exercises," *J. Neuroeng. Rehabil.*, vol. 9, no. 1, 2012, Art. no. 79.

- [26] É. O. Boyer, F. Bevilacqua, P. Susini, and S. Hanne-ton, “Investigating three types of continuous auditory feedback in visuo-manual tracking,” *Exp. Brain Res.*, vol. 235, no. 3, pp. 691–701, 2017.
- [27] A. Bregman, “Auditory scene analysis: The perceptual organization of sound,” *J. Acoust. Soc. Amer.*, vol. 95, Jan. 1990, Art. no. 1177.
- [28] G. Parseihian, S. Ystad, M. Aramaki, and R. Kronland-Martinet, “The process of sonification design for guidance tasks,” *J. Mobile Med.*, vol. 9, no. 2, pp. 1–24, 2015.
- [29] J. G. Neuhoff, “Is sonification doomed to fail?,” in *Proc. 25th Int. Conf. Auditory Display*, 2019, pp. 327–330.
- [30] S. D. H. Cornejo, “Towards ecological, embodied and user-centric design in auditory display,” in *Proc. 24th Int. Conf. Auditory Display*, 2018, pp. 191–196.
- [31] P. Vickers, “Sonification and music, music and sonification,” in *The Routledge Companion to Sounding Art*. New York, NY, USA: Taylor & Francis, 2016, pp. 135–144.
- [32] K. Vogt, D. Pirrò, I. Kobenz, R. Höldrich, and G. Eckel, “Physiosonic-evaluated movement sonification as auditory feedback in physiotherapy,” in *Auditory Display*. New York, NY, USA: Springer, 2009, pp. 103–120.
- [33] P. Susini, N. Misdariis, G. Lemaitre, and O. Houix, “Naturalness influences the perceived usability and pleasantness of an interface’s sonic feedback,” *J. Multimodal User Interfaces*, vol. 5, nos. 3/4, pp. 175–186, 2012.
- [34] S. Roddy and D. Furlong, “Embodied aesthetics in auditory display,” *Organised Sound*, vol. 19, no. 1, pp. 70–77, 2014.
- [35] P.-J. Maes, J. Buhmann, and M. Leman, “3MO: A model for music-based biofeedback,” *Front. Neurosci.*, vol. 10, Dec. 2016, Art. no. 548.
- [36] I. Bergstrom, S. Seinfeld, J. Arroyo Palacios, M. Slater, and M. Sanchez-Vives, “Using music as a signal for biofeedback,” *Int. J. Psychophysiol.*, vol. 93, pp. 140–149, 2014.
- [37] C. Henkelmann, “Improving the aesthetic quality of realtime motion data sonification,” Univ. Bonn, Bonn, Germany, Tech. Rep. CG-2007-4, 2007.
- [38] P. Vickers and B. Hogg, “Sonification abstraite/sonification concrete: An ‘aesthetic perspective space’ for classifying auditory displays in the ars musica domain,” in *Proc. 12th Int. Conf. Auditory Display*, London, U.K., 2006, pp. 210–216.
- [39] S. T. Mace, C. L. Wagoner, D. J. Teachout, and D. A. Hodges, “Genre identification of very brief musical excerpts,” *Psychol. Music*, vol. 40, no. 1, pp. 112–128, 2012.
- [40] A. J. Sihvonen, T. Särkämö, V. Leo, M. Tervaniemi, E. Altenmüller, and S. Soinila, “Music-based interventions in neurological rehabilitation,” *Lancet Neurol.*, vol. 16, no. 8, pp. 648–660, 2017.
- [41] M. H. Thaut and V. Hoemberg, Eds., *Handbook of Neurologic Music Therapy*. New York, NY, USA: Oxford Univ. Press, 2014.
- [42] A.-P. Andersson and B. Cappelen, “Musical interaction for health improvement,” in *The Oxford Handbook of Interactive Audio*. New York, NY, USA: Oxford Univ. Press, 2014, pp. 247–262.
- [43] M. Lesaffre, “Investigating embodied music cognition for health and well-being,” in *Springer Handbook of Systematic Musicology*. New York, NY, USA: Springer, 2018, pp. 779–791.
- [44] M. Gurevich and A. C. Fyans, “Digital musical interactions: Performer-system relationships and their perception by spectators,” *Organised Sound*, vol. 16, no. 2, pp. 166–175, 2011.
- [45] V. Lorenzoni, P. Van den Berghe, P.-J. Maes, T. De Bie, D. De Clercq, and M. Leman, “Design and validation of an auditory biofeedback system for modification of running parameters,” *J. Multimodal User Interfaces*, vol. 13, no. 3, pp. 167–180, 2019.
- [46] T. Fritz *et al.*, “Musical agency reduces perceived exertion during strenuous physical performance,” *Proc. Nat. Acad. Sci. United States Amer.*, vol. 110, pp. 17784–17789, Oct. 2013.
- [47] M. Schedel *et al.*, “Interactive sonification of gait: Realtime biofeedback for people with Parkinson’s disease,” in *Proc. Interact. Sonification Workshop*, 2016, pp. 94–97.
- [48] B. Moens *et al.*, “Encouraging spontaneous synchronisation with D-jogger, an adaptive music player that aligns movement and music,” *PLoS One*, vol. 9, 2014, Art. no. e114234.
- [49] M. Fabiani, A. Friberg, and R. Bresin, “Systems for interactive control of computer generated music performance” in *Guide to Computing for Expressive Music Performance*. New York, NY, USA: Springer, 2013, pp. 49–73.
- [50] A.-M. Raberger *et al.*, “Short-term effects of real-time auditory display (sonification) on gait parameters in people with Parkinson’s disease—A pilot study,” *Biosyst. Biorobot.*, vol. 15, pp. 855–859, 2016.
- [51] N. Nikmaram *et al.*, “Musical sonification of arm movements in stroke rehabilitation yields limited benefits,” *Front. Neurosci.*, vol. 13, 2019, Art. no. 1378.
- [52] N. Schaffert, T. B. Janzen, R. Ploigt, S. Schlüter, V. Vuong, and M. H. Thaut, “Development and evaluation of a novel music-based therapeutic device for upper extremity movement training,” *PLoS One*, vol. 15, 2020, Art. no. e0242552.
- [53] B. Yu, “Designing biofeedback for managing stress,” Ph.D. dissertation, Ind. Des. Dept., Tech. Univ. Eindhoven, Eindhoven, The Netherlands, 2018.
- [54] B. van derC. VlistBartneck, and S. Mäueler, “moBeat: Using interactive music to guide and motivate users during aerobic exercising,” *Appl. Psychophysiol. Biofeedback*, vol. 36, no. 2, pp. 135–145, Jun. 2011.
- [55] J. E. Boyd and A. Godbout, “Multi-dimensional synchronization for rhythmic sonification,” in *Proc. Int. Conf. Auditory Display*, 2012, pp. 68–74.
- [56] P.-J. Maes, V. Lorenzoni, and J. Six, “The SoundBike: Musical sonification strategies to enhance cyclists’ spontaneous synchronization to external music,” *J. Multimodal User Interfaces*, vol. 13, no. 3, pp. 155–166, 2019.
- [57] K. S. Park, C. Hass, B. Fawver, H. Lee, and C. Janelle, “Emotional states influence forward gait during music listening based on familiarity with music selections,” *Hum. Movement Sci.*, vol. 66, pp. 53–62, 2019.
- [58] D. Linnhoff, S. Alizadeh, N. Schaffert, and K. Mattes, “Use of acoustic feedback to change gait patterns: Implementation and transfer to motor learning theory—A scoping review,” *J. Motor Learn. Develop.*, vol. 8, pp. 598–618, 2020.
- [59] J. Dyer, “Human movement sonification for motor skill learning,” Ph.D. dissertation, Fac. Eng. Physical Sciences, Queen’s Univ. Belfast, Belfast, U.K., 2017.
- [60] T. Hermann, A. Hunt, and J. G. Neuhoff, *The Sonification Handbook*. Berlin, Germany: Logos Verlag, 2011.
- [61] D. Giansanti, M. Dozza, L. Chiari, G. Maccioni, and A. Cappello, “Energetic assessment of trunk postural modifications induced by a wearable audio-biofeedback system,” *Med. Eng. Phys.*, vol. 31, no. 1, pp. 48–54, 2009.
- [62] M. Rodger, W. Young, and C. Craig, “Synthesis of walking sounds for alleviating gait disturbances in Parkinson’s disease,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 543–548, May 2014.
- [63] P. R. Kantan, “A musical biofeedback system for balance and gait rehabilitation in hemiparetic stroke patients,” Master’s thesis, Dept. Architecture, Des., Media Technol., Aalborg Univ., Copenhagen, Denmark, 2020.
- [64] S. Balasubramanian, A. Melendez-Calderon, A. Roby-Brami, and E. Burdet, “On the analysis of movement smoothness,” *J. Neuroeng. Rehabil.*, vol. 12, 2015, Art. no. 112.
- [65] A. Hunt, M. M. Wanderley, and M. Paradis, “The importance of parameter mapping in electronic instrument design,” *J. New Music Res.*, vol. 32, no. 4, pp. 429–440, 2003.
- [66] T. Van Crielinge *et al.*, “The effectiveness of trunk training on trunk control, sitting and standing balance and mobility post-stroke: A systematic review and meta-analysis,” *Clin. Rehabil.*, vol. 33, no. 6, pp. 992–1002, 2019.
- [67] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, “Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review,” *Psychon. Bull. Rev.*, vol. 20, no. 1, pp. 21–53, 2013.
- [68] A. O. Effenberg, “Movement sonification: Effects on perception and action,” *IEEE Multimedia*, vol. 12, no. 2, pp. 53–59, Apr.–Jun. 2005.
- [69] J. F. Dyer, P. Stapleton, and M. Rodger, “Mapping sonification for perception and action in motor skill learning,” *Front. Neurosci.*, vol. 11, 2017, Art. no. 463.