Development of a biofeedback system using harmonic musical intervals to control heart rate variability with a generative adversarial network

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Abstract

Biofeedback methods supply biological information to subjects in real-time. Target biomedical/physiological variables are measured and fed back either directly, or transformed beforehand. Biofeedback based on Heart Rate Variability (HRV) has shown to have positive effects in managing anger, sleep, general quality of life and the restoration of physiological homeostasis. The literature suggests the use of new technologies to deal with interpreting the information and determining how Generative Adversarial Networks (GANs) might help in transforming information that flows through a biofeedback system. Given the wide use of Musical Instrument Digital Interface (MIDI) and piano-rolls, and the importance of HRV in the fields of health and perception, a GAN-based biofeedback system was proposed to generate MIDI sequences of harmonic musical intervals (HMI) from HRV signals. The proposed system seeks to produce, by changing HMI sounds, desirable respective HRV responses. The system was tested simulating HRV responses to HMI stimuli (the global health threat excluded real-life testing). Simulation was performed using a one-dimensional GAN. Rather than from latent space, one GAN generator was fed from raw HRV and the other from sound signals. An association was distinguished between the captured HRV signals and the stimuli, since GAN can generate representations similar to the stimuli employed. As a biofeedback system, the subjects provide HRV to feed the GANs and can be stimulated with sounds produced by an HMI generator. This system opens doors in the fields of perception and stress management, and might be applied in neuromarketing and human-computer interfaces.

Keywords: artificial intelligence, harmonic musical intervals, heart, MIDI, music, piano-roll

1. Introduction

Biofeedback is a method which supplies biological information to subjects in real-time, where a target biomedical variable - physiological or psychological - is measured and is fed back directly, or transformed beforehand [1]. Usually, physiological measurements are used to control specific systems, such as auditory or visual feedback methods [1]. Recently, biofeedback has captured the attention of researchers due to its potential in the health area. Biofeedback has been used as a non-pharmacological option and has even been considered when medicines have not provided the expected results; for instance, biofeedback has been utilized in the treatment of seizures [2], chronic pain [3], headaches [4], in the rehabilitation of vision [5] and amputation [6]. Among other uses, biofeedback is a promising application for helping people intolerant to medicines or where a medicine is contraindicated, such as in the case of paediatric populations [7], and pregnancy [8].

Biofeedback based on Heart Rate Variability (Bio-HRV) takes advantage of the ability of Heart Rate Variability (HRV) to reflect the function of the autonomic nervous system, as a balance between the sympathetic and parasympathetic nervous system [9]. An increase in HRV is associated with a parasympathetic domain, while a reduction in HRV is associated with a sympathetic prominence [10]. A reduced HRV has been linked to cardiovascular diseases, mortality risk [11], as well as brain impairment [11]; conversely, higher HRVs are associated with a good health condition [12]. Bio-HRV has shown good effects on the management and improvement of conditions such as anger, sleep, quality of life in general [13] and restoration of physiological homeostasis [14]. Post-traumatic stress disorder [15], anxiety [16], stress [17], and depression [18] have also been managed with Bio-HRV, as well as stress management for daily life [19]. Bio-HRV has further been used to improve performance in athletes [20] and even artistic performance [13]. Bio-HRV was seen to enhance conditions in healthy and unhealthy subjects when used as a complementary treatment [13] and has shown to be a promising alternative in treating chronic pain and fibromyalgia [21]. Commonly, biofeedback information is displayed to the subjects as a visual, vibrotactile, or more recently, gaming or virtual reality environment [1]. Biofeedback has also been implemented by using sound or music. For instance, biofeedback with music (Bio-mus) has been used to help subjects with Parkinson's disease [22] [23]. The use of feedback with electroencephalograms (EEG) of subjects to control music stimuli has produced a decrease in stress levels and normalization of their EEG [24].

In the field of biofeedback, some applications have been performed using Musical Instrument Digital Interface (MIDI). This is a protocol to carry out communication between electroacoustic instruments and emerged in the 1980s [25]. MIDI is a standard format largely used in the world of music, by including music production, composition, and computation. One example of biofeedback application is observed here [26], where an algorithm was developed to transform heart rate into MIDI data as pitch and note intervals. This MIDI data was played to subjects, whose heart rate was measured. Another example is presented in [27], where the breathing of subjects was measured and transformed into a tempo variable in a MIDI file. Subjects had to adjust their respiration to a generated accompaniment line in such a way that when the breathing was in the desired tempo, the sound generated was comfortable and harmonious. As the tempo of accompaniments went on decreasing, respiration likewise was slowing down each time. MIDI has been also used to translate movements into different types of sound in a biofeedback context for stroke patients [28] [29]; both examples expose the versatility of MIDI within a biofeedback environment to produce simple or complex sounds. Another biofeedback application [30] considered MIDI to map HRV data into timing variations of the sound. Four ways to present the auditory feedback were observed; the variations in R-R intervals were transformed into arpeggio chords with timing variation, arpeggio chords with emphasis variation, two distinct notes with RR interval delay, and stereophonic notes with RR interval delay.

Bio-HRV has shown great potentiality to help in the area of health with psychological and physiological diseases or conditions. With this fact in mind, Bio-HRV could be exploited to a larger extent and could even be applied in further research related to other topics, such as the perception of sound or music. This consideration emerges based on the fact that certain studies have shown that HRV is affected by exposition to sound or music [31] [32]. Despite the benefits observed with the use of the Bio-HRV, it is necessary to continue developing new applications and carrying out research to assess the capacity of those particular applications [13] [14] [33], such as biofeedback controlled by sounds. For example, biofeedback has shown its capacity to improve stress indicators, physiologically and psychologically. It is required, however, to conduct new research to determine the optimum components of biofeedback to guarantee and improve the effectiveness of its different applications [34]. A recent analysis of biofeedback implementations has shown that there is a lack of understanding of the mechanisms by which biofeedback training has shown good results, and this fact has prevented biofeedback from being included as a treatment of a number of diseases [35]. Literature has also suggested the use of new technologies to deal with the challenges in biofeedback systems, such as the interpretation of the biofeedback information [19]. In that order of ideas, it would be interesting to determine how Generative Adversarial Networks (GANs) could help in the transformation of the information that flows throughout a biofeedback system in such a way it could be more understandable for users.

Bearing in mind the wide use of MIDI and piano-rolls, and the importance of HRV in the field of health and perception, in this study a GAN-based biofeedback system was proposed to generate MIDI sequences from HRV signals. The MIDI sequences were generated by the implementation of GAN in a piano-roll format from HRV signals captured while subjects were listening to 24 different harmonic musical intervals - HMIs. HMIs are musical notes that are produced at the same time [36], and piano-roll is a matrix representation of music in which the vertical dimension depicts note pitch and the horizontal dimension depicts the time [37]. They are characterized by the distance in semitones between the musical notes, or by the ratio between the fundamental frequencies of those notes [36]. HMIs were included in this study because of their influence in the perception of dissonance and at the same time in the emotional response [38].

The proposed biofeedback seeks in the first instance to produce some foreseeable and stable HRV responses of subjects to the selected HMI sounds; this approach would help to establish a clear response of HRV to each HMI included. The system works in an infinite loop producing HMI stimuli generated from HRV responses to those stimuli. This procedure would allow the establishment of identifiable responses to each sound. The changes in the HMI stimuli or HRV responses should be carried out by changing the HMI set point or reference. In the second instance, after the system has been trained, it would allow inducing HRV into a desired state, selected by means of the reference. This is an exploratory proposal in which the goal is to change the HRV of subjects as a response to HMI sounds, based on the emotional response to those types of musical sound. This proposal only considered raw signals to avoid the inclusion of procedures in the feedback loop that can introduce a time delay in the system. However, HRV features could be introduced as an offline element of data analysis [39]. This approach was taken since there is still a need to explore the field of perception of musical sounds, especially HMIs, and how they are related to HRV [40].

In this proposal, GANs were also considered in an exploratory way. GANs were included as a part of the proposed biofeedback system since they have better performance with respect to autoencoders, less restrictions compared to Boltzmann machine, and less computational cost in comparison with techniques such as Markov chains [41]; this last characteristic is of great importance in the development of biofeedback systems in which computational cost plays an important role in the speed of the system response. GANs were selected also because they allow data generation without the knowledge of explicit real data distributions; moreover, for GAN implementation, it is not necessary to assume mathematical constraints [41]. Performance evaluation of the GAN systems continues to be a challenge and the objective comparison between the performance of applications is still a difficult task, mainly because there are no standard metrics nor standard evaluation procedures [42]. The performance of the proposed system is measured by considering the correlation between the real and generated samples of the HMI representations. Moreover, performance is also evaluated by considering the mean accuracy of discrimination for real and generated data (discriminator of GANs) [43]. The system was tested by simulation of HRV responses to HMI stimuli. This simulation was carried out through a one-dimensional GAN. This GAN was trained with the experimental data to produce HRV signals with similar distributions to the measured signals. Unlike common applications of GANs, in this research, rather than from latent space, one of the GAN generators was fed from raw HRV and the other from sound signals used in the experimental phase. Latent space is a low-dimensional and nonlinear representation of data [44]. The HMI sounds were thus related to the HRV generated.

The remainder of this paper is structured as follows: Section 2 presents the methodology followed to achieve the proposed goal, in which signal processing procedures, GAN implementation, and the biofeedback proposal are detailed; Section 3 shows the main outcomes of this approach; Section 4 presents the discussion of the results; and finally, Section 5 gathers together the conclusions about the main elements of the work.

2. Methodology - Materials and Methods

2.1 Experimental design and data acquisition

After undergoing an audiometry assessment, 26 subjects were voluntarily enlisted, signing a consent form approved by the Internal Ethical Committee of the University of Cauca. The entire experimental protocol was carried out under the Declaration of Helsinki. A set of 17 males and 9 females formed the population sample, with a mean age of 25.3 ± 7.1 years.

Having signed the informed consent form, the subjects received instructions on the experimental procedure. In the course of the experiment, they adopted a supine position while a set of 24 HMIs was presented in random order. All stimulus sounds were played using noise-cancelling headphones. The 24 HMIs were formed by 12 synthetic harmonic sounds, 10 seconds of duration, in two different octaves: octave two ranged from note A2 to A3, and octave four ranged from note A4 to A5. Additionally, a period of silence of 15 seconds was left between each sound. As the sound stimuli were presented, ECG signals from lead II were recorded (**Fig 1**). Bearing in mind that normal ECG signals have a frequency band between 0.05–100 Hz [45], and taking into account the Nyquist theorem for sampling rate, ECG signals were acquired with a sample rate of 250 Hz [46] [47], since both low and high frequencies are thus preserved much to the same extent as with a sampling rate of 500 Hz (they are statistically similar) [48]; moreover, 250 Hz is considered the minimum accepted sample rate for HRV analysis [49].

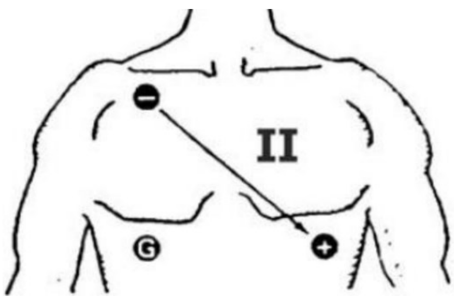

Fig 1. Electrode placement of the lead II ECG signal [50]

2.2. Signal processing

The recorded signals were pre-processed by applying a third-order, one-dimensional median filter to extract the signal trend. This trend was subtracted from the original signal, after which procedure signal filtering was performed, applying a notch filter of 60 Hz to remove electrical noise derived from the ac line potential (voltage).

Once the signals were pre-processed, R-peaks were segmented using the Pan–Tompkins algorithm [51]. Undetected peaks were marked manually. HRV was computed by finding the difference in milliseconds between each detected R-peak [52]. This difference between R-R intervals (tachogram) is considered as a representation of HRV in this proposal. While heart rate is the number of heartbeats in a period of time [39], HRV is the difference in time between consecutive heartbeats [39]. After HRV was computed, data was resampled from 2500 to 100 samples, and normalized so that the outcome had a mean equal to zero and a standard deviation equal to one. Even though this procedure might be seen as extreme, this down-sampling process holds onto the information between R-R intervals. This was carried out in a period of ten seconds, in which there were no more than 15 R-peaks. The complete steps performed in the signal processing phase are shown in Fig 2.

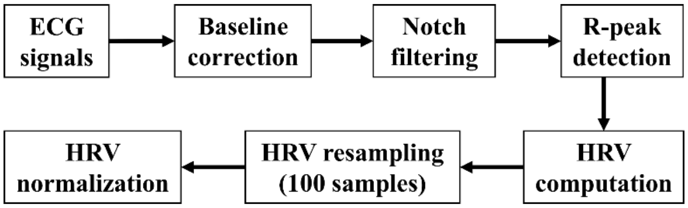

Fig 2. Complete steps performed in the signal processing phase

2.3. GAN implementation: GAN-1

To achieve the planned goal, a GAN system was implemented. A conditional GAN (HMI-GAN-1) was developed (**Fig 3** and **Table 1**) to generate piano-roll representations of MIDI sounds from HRV data. This GAN was formed by a generator and a discriminator. The generator was trained to generate synthetic piano-roll samples conditioned on sound labels corresponding to the HMIs used. The generator was fed with HRV signals, with 100 samples each. These signals were captured during the described experiment - *Section 2.1 Experimental design and data acquisition* - while the subjects were listening to HMIs in accordance with the sound labels.

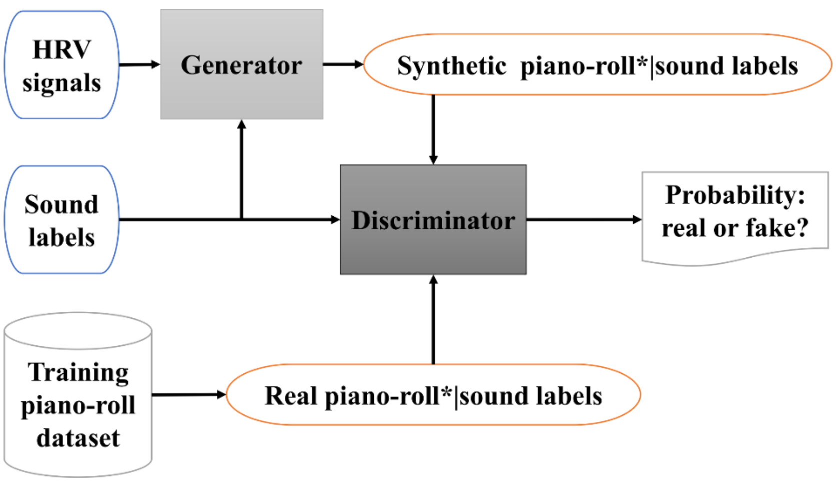

Fig 3. Diagram of the implemented HMI-GAN-1

Table 1. Architecture of GAN-1: generator and discriminator

Generator	Discriminator
Fully connected layer Dense(256 * 7 * 7, input_dim=100) Reshape((7, 7, 256))	***Convolutional layer*** Conv2D(64, kernel_size=3, strides=2, input_shape=(img_shape[0], img_shape[1], img_shape[2] + 1), padding='same')
Transposed convolution layer Conv2DTranspose(128, kernel_size=3, strides=2, padding='same')	***Leaky ReLU activation*** LeakyReLU(alpha=0.01)
Batch normalization BatchNormalization()	***Convolutional layer*** Conv2D(64, kernel_size=3, strides=2, input_shape=img_shape, padding='same')
Leaky ReLU activation	

Generator	Discriminator
LeakyReLU(alpha=0.01) ***Transposed convolution layer*** Conv2DTranspose(64, kernel_size=3, strides=1, padding='same') ***Batch normalization*** BatchNormalization() ***Leaky ReLU activation*** LeakyReLU(alpha=0.01) ***Transposed convolution layer*** Conv2DTranspose(1, kernel_size=3, strides=2, padding='same') ***Output layer with tanh activation*** Activation('tanh')	***Batch normalization*** BatchNormalization() ***Leaky ReLU activation*** LeakyReLU(alpha=0.01) ***Convolutional layer*** Conv2D(128, kernel_size=3, strides=2, input_shape=img_shape, padding='same') ***Batch normalization*** BatchNormalization() ***Leaky ReLU activation*** LeakyReLU(alpha=0.01) ***Output layer with sigmoid activation*** Flatten() Dense(1, activation='sigmoid') ***Training options*** loss='binary_crossentropy' optimizer=Adam()

The discriminator was trained to learn to recognize both real and synthetic samples and also sample-label pairs. In this case, 24 classes were considered by bearing in mind the HMIs used in the experimental phase, with a total of 56 samples per class. The discriminator receives real examples with labels (Real piano-roll*|sound labels), as well as synthetic samples with labels (Synthetic piano-roll*|sound labels) that are produced by the generator. The discriminator then produces an output indicating a probability that the observed input samples are real and matches them with their labels.

At this point, using this methodology it was possible to reconstruct HMI representations from the HRV changes produced as a result of the HMI stimuli. Thus, after training HMI-GAN-1, it could be used to produce HMIs from HRV signals not used in the training stage. This methodology could then be used in future research to develop algorithms to produce a more highly developed music from the HRV data gathered from people. Consequently, it may even be possible to listen to HRV.

2.4. Biofeedback proposal

A biofeedback system is proposed based on the implemented generator of HMIs (HMI-GAN-1). This system seeks to produce changes in the HRV of subjects in a differentiable manner by using HMI sounds as a control/regulator element. The HMI-GAN-1 generator is used here to transduce HRV signals into HMIs (HMI-T). The HMI-T will serve as a reference for a generator of HMI sequences (HMI-sequencer). Finally, these sequences will be presented as sound to the subjects.

In this system, HRV measurements are taken over a determined period (at least five seconds) in cycles with an established duration (at least 30 seconds are suggested). These measurements are saved in the memory and a mean signal is computed from them. The mean HRV signal is presented to the trained HMI-GAN-1 and produces an HMI. A user input or HMI generated serves as HMI reference and feeds the HMI-sequence generator. This generator produces HMI sequences with the reference HMI; for instance, if the reference HMI is a major third, the produced sequence will have only this type of interval (**Fig 4**).

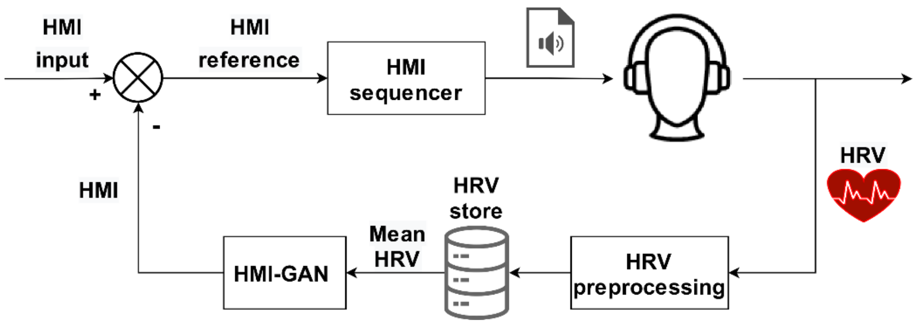

Fig 4. Detailed block diagram of the biofeedback system

The HMI-sequence generator takes a random musical note for constructing the first HMI of a new sequence. The other note of this first HMI note is chosen above the first note. The next HMIs will be formed by following the changes in a random or Brownian motion model. While values in the model are increasing, the HMIs will be constructed above, and vice-versa. HMI tones in sequences must be produced far enough from each other in time so that next HMI tone does not arrive in the short-term memory before the previous sound has left it. Thus, in order to concentrate on the harmonic character of the HMI stimuli, it is necessary that the stimuli are formed by sequences of HMI tones with a duration of 800 ms followed by silences of 1200 ms [53]. This could be repeated in the order of five times. Each sequence should have a minimum duration of ten seconds but should not be too long to avoid a state of stress in the listener. The minimum duration is based on the fact that the literature does not report ultra-short HRV recordings less than ten seconds [54]. A duration of less than ten seconds may nevertheless allow the system to search for responses of HRV to the presented stimuli. The system will generate different HMI sequences in which each will include the same type of HMI tones but in different pitches. In this sense, despite the fact that it would be possible to find a response particular to each HMI tone in accordance with its pitch, the main idea behind this approach is to discover a general reaction to the HMI tones belonging to the same type, i.e. HMI sequences.

3. Results

3.1. HMI-GAN-1

In order to create a bi-dimensional depiction, a piano-roll representation was made from the sound stimuli used in the experimental procedure. It was thus possible to present the real samples as a training dataset to HMI-GAN-1, and this could then generate the data as a piano-roll format. The mean accuracy of discrimination for real data was 0.53, and for generated data 0.52 (Table 2); from which it is deduced that the system was not able to differentiate completely between real and generated data, suggesting a good performance in generating new data. A sample of data used for training, in the lower octave, and another generated by the HMI-GAN-1 is shown in Fig 5.

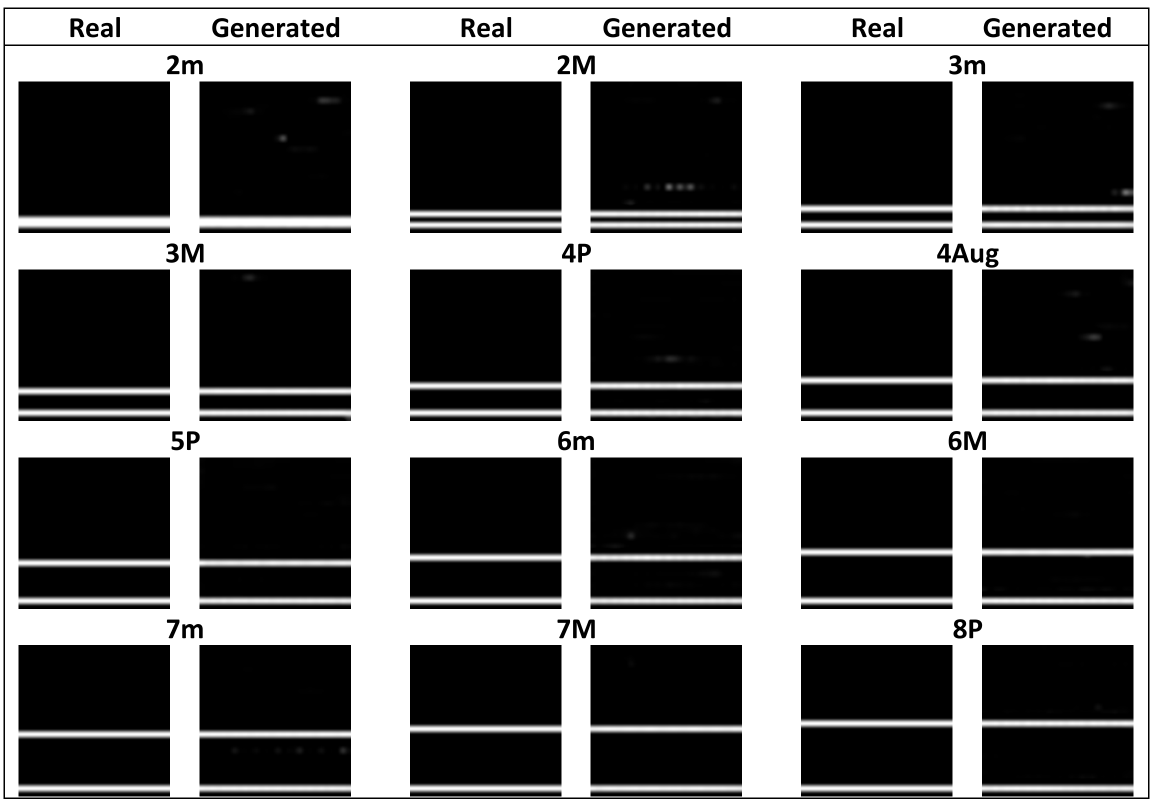

Fig 5. Piano-roll representation of HMIs for the lowest octave in the real and generated dataset

Correlation between the real and generated samples

Similarity between the real and generated samples was assessed by computing the correlation coefficient between them, providing values of between 0.95 and 0.99, with a mean of 0.99 (Fig 6, Table 2).

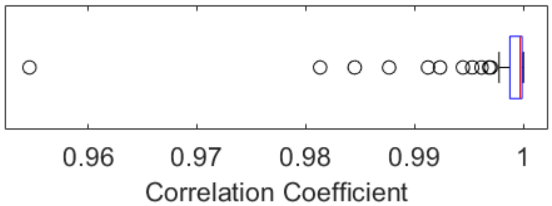

Fig 6. Box plot of the correlation coefficients between the real and generated data

Table 2. Performance metrics for HMI-GAN-1: accuracy and mean of correlation coefficients

Accuracy		Correlation coefficient
Real data	Generated data	(mean)
0.53	0.52	0.99

3.2. Evaluation of biofeedback proposal by simulation: GAN-2

After implementation of HMI-GAN-1, it is necessary to assess the biofeedback proposal. Having closely observed the HMI-GAN-1 performance, one way to assess the biofeedback would be by means of a simulation of HRV responses to HMI sounds. This goal in mind, a GAN system was implemented to generate HRV data from HMI sounds. This system followed the same methodology described in *Section 2.3. GAN implementation*. However, in this case, the generator of a second GAN (GAN-2, Table 3) was trained to generate HRV data while it was fed with audio data instead of data from latent space. The mean accuracy of discrimination for real data was 0.56, and for generated data, 0.51 (Table 4); this means that the system was not able to differentiate completely between real and generated data, suggesting a good performance in generating new data. The HRV real data to train the GAN-2 (Fig 7 – red graphs) was processed in the same manner as described in *Section 2.2. Signal processing*, and was captured as the subjects listened to the audio stimuli that served to feed the implemented GAN. The data generated by GAN-2 (Fig 7 – blue graphs) followed distributions similar to the real data, simulating a response to the sound data utilized to feed the GAN.

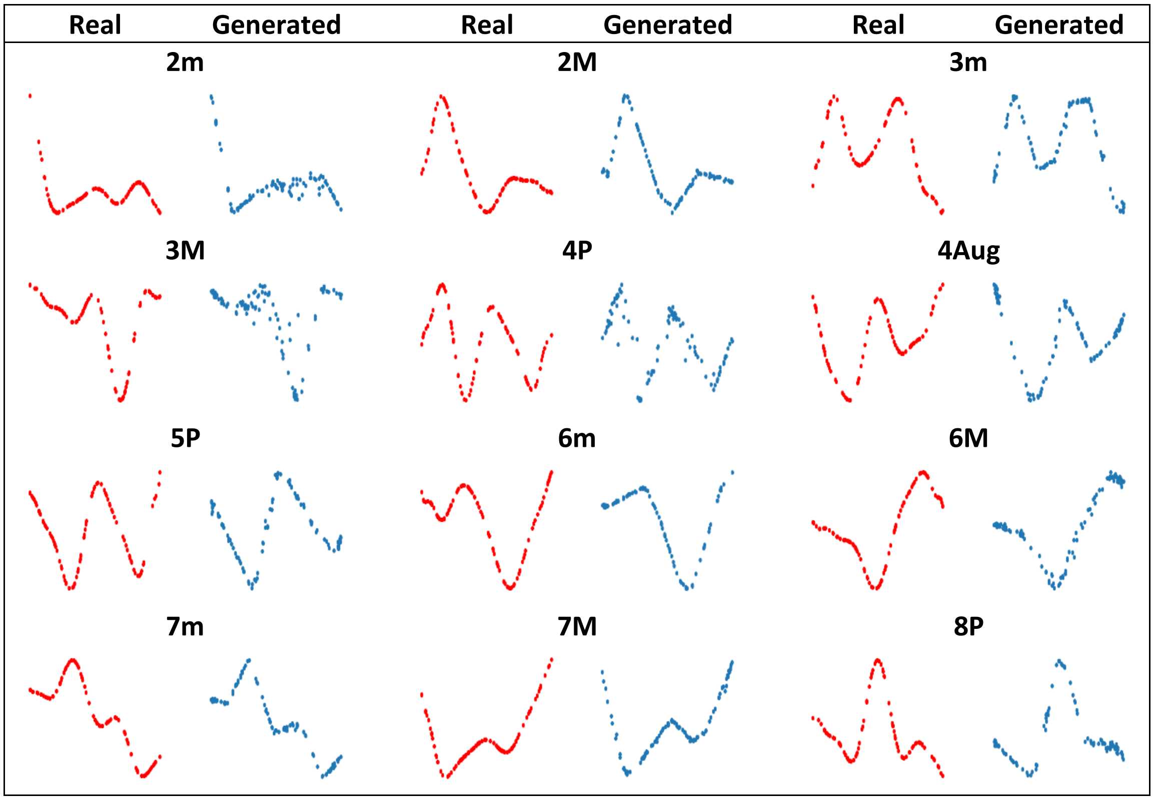

Fig 7. HRV data used to train the GAN (real data: red) and the data generated simulating a response to HMI sounds of the lower octave (generated data: blue). In each figure, the vertical axis represents the time of the RR intervals (between 800 and 1200 ms) and the horizontal, number of samples (n). These axes are omitted to facilitate visualization.

Table 3. Architecture of GAN-2: generator and discriminator

Generator	Discriminator
Fully connected layer Dense(70, activation='relu', kernel_initializer='he_uniform', input_dim=latent_dim)	***Fully connected layer*** Dense(25, activation='relu', kernel_initializer='he_uniform', input_dim=n_inputs)
Output layer with linear activation Dense(outputs = 2, activation='linear')	***Output layer with sigmoid activation*** Dense(1, activation='sigmoid')
	Training options loss='binary_crossentropy' optimizer=Adam()

Table 4. Performance metrics for GAN-2: accuracy

Accuracy	
Real data	Generated data
0.56	0.51

4. Discussion

From the outcomes, it is possible to observe that the implemented GAN was able to generate the piano-roll representation of the HMIs from the HRV captured at the same time as the HMIs were presented to the subjects. It is important to note that the GAN was able to produce the expected results although being fed from HRV signals rather than the more traditional samples from latent space. In this proposal, the correlation coefficient was introduced as a metric to assess the performance of the system. A minimum correlation coefficient of 0.95 was found between the real and the generated samples, indicating a high similitude between them. Both GANs, HMI-GAN-1 and GAN-2, produced in its performance an accuracy close to 0.5 for real and generated data. Despite the fact that in traditional classification tasks this value represents the worst of the cases, in the context of GANs, this is associated with a good performance since the system is not able to classify or differentiate between the real data and the data produced by the generator of the GAN. This means that the generator is thus able to produce new data with similar features to the real data from which it was trained.

The performance of the first system -HMI-GAN-1: accuracy≈0.5- suggests that the HMI representations produced by the generator are similar to the real data, and the system is able to produce this data from the HRV used to feed the generator. Furthermore, due to it being possible to generate a representation of the presented stimuli, one possible conclusion is that the HRV response was affected by those stimuli. GANs could be observed as a method of correlation or association between the stimuli presented and the effects produced. The performance of the second system - GAN-2: accuracy≈0.5- suggests that the system was able to simulate the HRV response to HMI stimuli. The samples of HRV simulated follows the distributions of the samples used to train the system, data actually associated with HMI stimuli. Due to the fact that GANs were used as an HRV simulator; as such, they might go on to be used in applications to simulate HRV under several circumstances. In our particular application, they were able to simulate the HRV response to HMI stimuli.

The outcomes of this study can be considered important since they represent a way in which to associate HRV response with HMI stimuli, an outcome relevant to the field of perception and to their future application in a number of other fields. This system might go on to have applications in neuromarketing as well as in human-computer interfaces. Given that HMIs have a great capability for producing emotional responses, GANs could perhaps be utilized to reinforce an emotional state identified using HRV, or perhaps even change that state for another preferred state. In this way, applications in neuromarketing or human-computer interfaces could approach more closely the user's emotions through sounds that take advantage of HMIs. As regards possible applications of this biofeedback proposal, these might well be found in research in which emotions are linked to HMIs. Additionally, research to associate HMIs with HRV metrics could be continued. Finally, the biofeedback system could be used in applications related to the practices of such as Yoga and Meditation as well as in sessions of specialist music therapy.

Due to the difficulty of the task of performance evaluation of the GAN systems [42], a comparison of this proposal with other systems reported in the literature cannot be made in an objective manner. Previous applications of biofeedback through sound have performed the sonification of a physiological variable and fed back to the subject. Variables such as movement [28] [29], respiration [27], and cardiac activity [26] [30] have been used as a source of sonification. Unlike these previous approaches, this proposal does not perform a direct sonification of the physiological variable in question (HRV). Instead, the variable of interest is transformed into a musical sound that is in turn associated with the responses to this variable themselves. Another difference lies in the fact that, in previous applications, the subjects consciously interact with the biofeedback system by deliberately adjusting the measured variable. In the proposed system, the variable of interest is manipulated by the setpoint and the subjects do not have the need to interact directly with the system. Although studies related to biofeedback systems are well established for HRV in health applications, the inclusion of HMI as feedback stimuli and GANs as part of the system has not been extensively studied. This proposal seeks in a preliminary manner to extend the application of biofeedback systems for understanding additionally the effect of specific musical structures.

A recent application [55] studied the effect of sound biofeedback as a method for reducing stress using HRV as the observed variable. It was noted that sound is able to produce changes in HRV, and this might be used in well-being applications such as the one herein presented. Sounds imitating heart rate were used as stimuli, contrary to the approach presented in this document, in which HMI sounds associated with HRV responses were supplied to the subjects in HMI form. A closer idea to the approach presented in this manuscript was considered in [56] in which heart rate was transformed using falling water sounds before being fed back to the subjects; while the authors transformed the variable of interest into water sounds, in this proposal the variable of interest was transformed into HMI sounds. HRV was similarly considered in [57] as a variable to change or produce sound interactively; the main difference with the approach herein is that while frequency domain methods were used to analyse data, the proposal shown here considered signals in the time domain. A further interesting study is observed in [58], wherein in addition to heartbeat sound, subjects received haptic feedback from their own heartbeat; in this case, HRV showed changes as a response to heartbeat vibration. The authors made direct use of heartbeat sounds as a biofeedback method, while in the present work, feedback elements were transformed into a completely different type of sound – HMI. It should be noted that in the haptic feedback study no effects of heartbeat sounds were found.

Another architecture found in the literature includes a musical generator in a biofeedback system [59], implementing a system to record galvanic skin response (GSR) from subjects as they listened to music generated by Hidden Markov Models. The music was labelled according to the emotions it could evoke, serving as a biofeedback control able to generate new music through a machine learning algorithm. This approach largely agrees with the present manuscript - both structures propose a biofeedback system in which the measured variable is transformed into a musical element to be presented to subjects. In this way, the measured variable is transduced completely from a biological signal into a sound stimulus; subjects do not interact in a direct manner with the recorded variable. Finally, the differences consist in the biological variables considered, namely GSR as opposed to HRV in this proposal. In contrast that work and previous implementations, this proposal incorporates GANs as part of the biofeedback system. As can be noted, the present biofeedback proposal incorporated HRV as the variable of interest and transformed it into sound stimuli, mixing some elements presented in previous literature. However, the inclusion of specific elements of music – HMI - and GANs can be highlighted as new aspects in biofeedback systems. These might be explored in future research as well as applications.

One limitation of the proposed system is related to the inclusion of HMI stimuli framed within a western context. As such, the results obtained may not be easily generalized to the eastern context, in which eastern people could have a different psychophysiological response to these same stimuli. In this case, the system should be adjusted by changing the selection of the stimuli by including other types of HMI. As a part of future work to improve this proposal, the development of specific metrics is taken into account in order to measure the performance of each GAN. In this manner, these metrics ought to provide a better interpretation of the GAN performance in this context and also work well in the feedback loop. Future work also might include the use of other HRV features to analyse data or also as a part of the biofeedback system. The literature shows several features in the frequency domain (LF, HF, LF/HF ratio), time domain (RR interval, HR (bpm), SDNN), and nonlinear domain that can be included [39]. Our previous study shows that HMIs in fact can produce variations in the heart response, observable via different features [60]; in this manner, for instance, the present proposal might be focused on the study of a concrete HRV feature.

5. Conclusions

A system was built to generate MIDI files with a piano-roll representation from HRV signals captured while presenting HMIs to subjects. From the outcomes it was possible to find an association between the HRV signals captured and the stimuli presented, since the GAN network was able to generate very similar representations to the stimuli used in the real experiment. Based on the piano-roll generator, a biofeedback proposal was presented. This biofeedback was simulated via a GAN system, in which HRV signals were produced from sound stimuli. The proposed system shows the potential to be applied as a biofeedback system. In such a system, subjects are the source of HRV to feed the GANs. At the same time, those subjects can be stimulated with the sounds produced by a generator of HMIs. In this way, HRV in the subjects could be modified as the generated sounds change. Bearing in mind that the inclusion of HMI as feedback stimuli and GANs as part of the system has not been extensively studied, the proposed system represents a possibility to continue with research in fields such as perception and management of conditions such as stress. Moreover, that proposal could be applied within future applications in neuromarketing and HCI.

CRediT authorship contribution statement

Ennio Idrobo-Ávila: conceptualization, methodology, software, literature review, writing - original draft, writing - review & editing. **Humberto Loaiza-Correa:** supervision, reviewing. **Flavio Muñoz-Bolaños:** supervision, reviewing. **Leon van Noorden:** conceptualization, reviewing and editing. **Rubiel Vargas-Cañas:** conceptualization, methodology, supervision, reviewing and editing.

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Conflict of interest statement
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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