MAPPING INTER-CARDIOVASCULAR TIME-FREQUENCY COHERENCE TO HARMONIC TENSION IN SONIFICATION OF ENSEMBLE INTERACTION BETWEEN A COVID-19 PATIENT AND THE MEDICAL TEAM

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ABSTRACT

This paper presents exploratory work on sonic and visual representations of heartbeats of a COVID-19 patient and a medical team. The aim of this work is to sonify heart signals to reflect how a medical team comes together during a COVID-19 treatment, i.e. to highlight other aspects of the COVID-19 pandemic than those usually portrayed through sonification, which often focuses on the number of cases. The proposed framework highlights synergies between sound and heart signals through mapping between time-frequency coherence (TFC) of heart signals and harmonic tension and dissonance in music. Results from a listening experiment suggested that the proposed mapping between TFC and harmonic tension was successful in terms of communicating low versus high coherence between heart signals, with an overall accuracy of 69%, which was significantly higher than chance. In the light of the performed work, we discuss how links between heart- and sound signals can be further explored through sonification to promote understanding of aspects related to cardiovascular health.

1. INTRODUCTION

The COVID-19 (coronavirus disease 2019) pandemic has affected the world in many ways, not only in terms of world health, but also in relation to public understanding and access to health data. As the number of COVID-19 cases surged all over the world, a need to explain and interpret the health metrics communicated in news broadcasts also unfolded. The pandemic has highlighted the need to ensure that everyone has access to information on equal terms, which in turn has given rise to new attempts towards making health data more accessible to everyone, including those with visual impairments (see e.g. the review of the accessibility of statistical charts about COVID-19 for people with low vision, published in [1]). As a result, numerous attempts to present accessible data through sonifications of COVID-19 data have been presented this year (see e.g. [2, 3]). The majority of these sonifications have focused on progression of the pandemic through monitoring of number of positive cases or deceased (see e.g. [4–6]), and genomes and spike proteins, i.e. the protein that gives COVID-19 its characteristic crown-like appearance [7–11]. Although some attention has been given to portrayal of other effects of the pandemic, for example reduced air pollution in times of COVID-19 [12], little work in this context has focused on aspects related to the experiences of the patient and health workers who are directly impacted by the pandemic.

In the current work, we propose to use sonification and visualization to portray heartbeats of a medical team and a patient with COVID-19 during treatment. The aim is to explore time-frequency coherence (TFC) and heartbeat rhythms within this group, and to highlight how the medical team comes together as a whole to support the patient, through sonic representations. Through this work, we aim to highlight similarities between heartbeat signal analysis and audio signal analysis through mappings from inter-cardiac time-frequency coherence to harmonic dissonance in musical representations. Moreover, the ambition is to encourage future discussions on the potential benefits of heartbeat sonifications focused on mappings to musical parameters, and how such work could aid in creating an understanding of cardiovascular signals for those without bio-signal analysis backgrounds. Finally, the aim is to highlight another aspect of the the pandemic, i.e. how a medical team works together to support a patient suffering from COVID-19, and how this can be viewed (and heard) in the form of time-varying rhythmic and harmonic tension transformations in a music representation.

In this paper we first provide an overview of the spectral components of heart signals and explain the connection between such signals and music structures. We then propose a framework for sonification based on mapping time-frequency coherence to harmonic tension. We subsequently evaluate our work through a listening experiment and discuss classification accuracy for sonifications generated using the proposed framework, to evaluate if the suggested model successfully could communicate if two heart signals are coherent versus non-coherent. Finally, we discuss implications of the obtained results and suggest directions for future work focusing on communication of cardiovascular features through sounds.

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2. BACKGROUND

Music and heart signals share several common characteristics. The idea of drawing parallels between music and heart signals is not new; academic physicians wrote about the music of the human pulse already in the Middle Ages [13], and the first use of music notation to describe cardiovascular anomalies was done by the inventor of the stethoscope [14]. Physiological measures such as respiration, blood pressure and heart rate have been shown to increase and decrease with music tempo [15, 16]. The similarities between the human pulse and music means that heart signals can be readily mapped to music; for example, arrhythmias and other heart conditions are highly musical, considering their innate periodicity and time varying musical structures [17]. A set of collage pieces made by merging music excerpts that match segments of electrocardiogram (ECG), resulting in music that mirrors arrhythmia sequences, was presented in [18]. Other examples of mappings between heart data and music include [19–23]. For an overview of making music with heart signals, please refer to [17] and [24].

Previous work on sonification of cardiovascular features has largely focused on electrocardiography, the process of producing an electrocardiogram (ECG). An electrocardiogram is a visual representation in the form of a graph depicting voltage versus time of the electrical activity of the heart, which can be measured using electrodes placed on the skin. Two main research directions can be identified in sonification research on ECGs (see [25] for a systematic review on the topic): 1) sonifications of temporal features and 2) sonifications of certain pathological states corresponding to changes in waves that compose the ECG signal, i.e. processes serving as supporting tools in diagnosis tasks [26]. The first of the two categories involves sonifications focusing on monitoring heart rates [27, 28], which is primarily used in applications in sports, while the second focuses on measures of heart rate variability (HRV) [29–34], i.e. beat to beat variance measures[1]. Other examples of sonifications of cardiovascular health data include sonic representations of systolic and diastolic blood pressure [35] and pulse oximeter data [36, 37].

A common way of assessing activity of the autonomic nervous system (ANS) is to analyze the heart rate variability (HRV), which corresponds to ”the degree to which the time interval between successive heart beats fluctuates” [38]. The autonomic nervous system is the part of the nervous system that regulates involuntary action, such as activity of the intestines, heart, and glands [39]. It is usually divided into the sympathetic nervous system, which controls responses to stressful situations, and the parasympathetic system, which controls bodily functions when a person is at rest[2]. HRV usually presents two oscillations, one with central frequency in the range 0.15-0.4 Hz, and one with central frequency in the range 0.04-0.15 Hz [40]. The first oscillation is linked to vagal parasympathetic activity, whereas the second oscillation is related to both sympathetic and parasympathetic activity. In the analysis of HRV signals, the estimation of spectral coherence, i.e. the degree of correlation between the spectral components of two signals [41], in the joint time-frequency domain can be used to assess degree of similarity between two signals over different frequencies. In other words, this can be used to evaluate HRV coupling between two individuals' heart signals. In the current work, time-frequency coherence (TFC) analysis is used for the purpose of characterization of such dynamic cardiovascular interactions. For more details, see [42], and Sec. 3.2.

A central aspect of the work presented in this paper was to highlight how the medical team came together when treating the COVID-19 patient. As such, our work connects to previous research on synchronization and entrainment, i.e. the process by which independent rhythmical systems interact with each other, which may in turn result in systems synchronising [43]. Entrainment has been investigated in a variety of contexts, ranging from body movement to perceptual music research (see e.g. [44]). For example, studies on synchronized movements performed in pairs have suggested that periods of the interaction when both participants reported high *togetherness* were associated with increased cardiovascular activity and high correlation between heart rate time series [45]. Research on inter-cardiovascular time-frequency coherence has also shown that HRV synchronizes when non-experts sing together [46]. Most of this effect could be attributed to respiratory sinus arrhythmia, however, some HRV synchronization persisted when the effect of respiration was removed using spectral decomposition [47, 48].

In the current work, time-frequency coherence of heart signals are mapped to harmonic tension in the spiral array, a model for tonality in the form of a 3D representation of pitch classes, chords and keys [49]. In the spiral array, each pitch class is represented as spatial coordinates along a helix [50], see Fig. 1. Notes that sound tonally close are positioned close to each other inside the array. For example, a C major chord only consists of spatially close pitches. In the spiral array, notes are arranged so that consecutive notes are one perfect fifth from each other, corresponding to a quarter turn in the spiral, resulting in notes positioned above each other representing a major third [49]. Three methods for quantifying aspects of tonal tension based on the spiral array are presented in [51], one of them being the *cloud diameter*, which captures the largest distance between any two notes in a cloud. If a cloud of notes contains intervals that are dissonant, i.e. tonally far from each other, the distance in the spiral array will be large. In this way, Euclidean distance within the cloud can be used as a measure of harmonic tension.

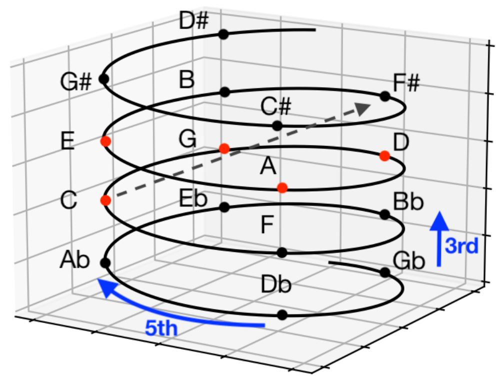

Figure 1: Distances in the pitch class helix of the spiral array. The pentatonic scale used as reference is highlighted in red, since this was one of the sets of pitches used to sonify the patient's heartbeats. The dotted arrow shows the distance from C to F♯, which are tonally far from one another.

[1] Heart rates are not constant; they vary, even from beat to beat.

[2] This is a somewhat simplified explanation; in reality these relationships are more complex.

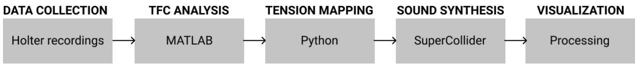

Figure 2: Visualization of the workflow.

3. METHOD

An overview of the workflow is displayed in Fig. 2. The separate stages of the process are described in detail below.

3.1. Data Collection

Holter recordings of 98 minutes on average[3] were collected from one patient and five persons from the multidisciplinary team involved in the ward round in the COVID Intensive Care Unit. The team was led by a cardiothoracic anaesthetic consultant, who was accompanied by one cardiology registrar, a junior intensivist, a physiotherapist, and a senior nurse. The patient and the medical team gave their explicit consent to their data being collected. The patient had a heart transplant, meaning that he had low autonomic tone, resulting in faster heart rate and low heart rate variability. The patient suffered from an autoimmune disease, was wheelchair bound, and had a tracheostomy resulting in difficulties speaking. After automatic extraction of the QRS complex [52], the R peaks were manually checked against the ECG and corrected in Sonic Visualiser [53]. The data was synchronized based on the starting times of the Holter recordings, which were precise to the minute. After data cleaning and alignment, the total duration of the recordings was 64 minutes, which is the total overlap between the ECG signals. Heart rates (in beats per minute) of the patient versus the medical team are visualized in Fig. 3. Descriptive statistics are presented in Tab. 1.

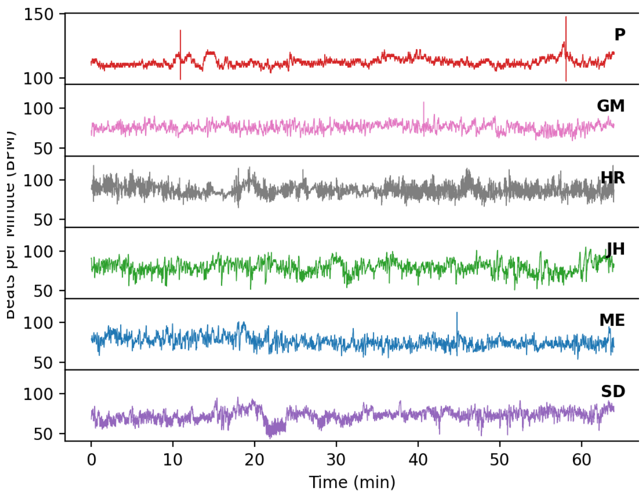

Figure 3: Heart rates (in beats per minute) of the patient (P, in red) versus the medical team members.

[3]Durations after cleaning, before alignment. End times varied within the medical team.

Person	Mean	Median	Min	Max	SD
P	112.24	111.30	97.22	147.69	3.18
GM	76.06	76.04	59.08	108.17	5.16
HR	86.90	86.29	64.54	118.15	6.44
JH	79.47	79.18	50.86	105.21	8.01
ME	75.80	75.29	53.33	112.94	7.06
SD	72.69	73.14	42.91	96.00	7.26

Table 1: Descriptive statistics of heart rates (beats per minute) of the patient (P) and the medical team members.

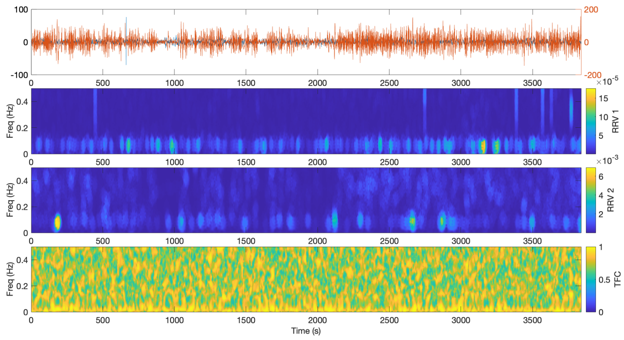

Figure 4: Results for patient versus medical team member HR. The top plot shows the original cardiovascular signals, RRV1 shows HRV (in ms) for the patient, RRV2 shows HRV for person HR, and TFC shows TFC (MTSP).

3.2. Time-Frequency Coherence Analysis

Instantaneous heart rates (in ms) were obtained from the cleaned R peaks extracted from the ECG data. When present, ectopic beats and artifacts were interpolated. Instantaneous heart rate series were re-sampled at 4 Hz and HRV signals were obtained by high-pass filtering the series with a cut-off frequency of 0.03 Hz. The methodology used to obtain time-frequency coherence between the two cardiovascular signals for the patient and each member of the medical team was based on multitaper spectrogram (MTSP) (see [42]). A summary of the analysis outcome is displayed in Fig.4. The results obtained were averaged over frequencies, using the full range (0.03 - 1.00 Hz). An overview of the average time-frequency coherence is displayed in Fig. 5. Descriptive statistics are presented in Tab. 2. A plot displaying mean TFC for the patient versus medical team member HR is shown in Fig. 6. The reader is encouraged to listen to the two sonifications of these excerpts to hear the difference in dissonance for the two curves[4].

3.3. Mapping to Harmonic Tension

Distances in the spiral array were computed using functions defined in the Python implementation of the spiral array model by Rui Guo[5], which is further described in [54].

[4]Supplementary material is available from https://drive.google.com/drive/folders/17z2m3xwkK-ySipwrU6UHoxXR5BxU9hmp?usp=sharing. For this particular example, see files in the *audio* folder starting with *"fig5_noncoh"* versus *"fig5_coh"*.

[5]See https://github.com/ruiguo-bio/midi-miner/blob/master/example.ipynb.

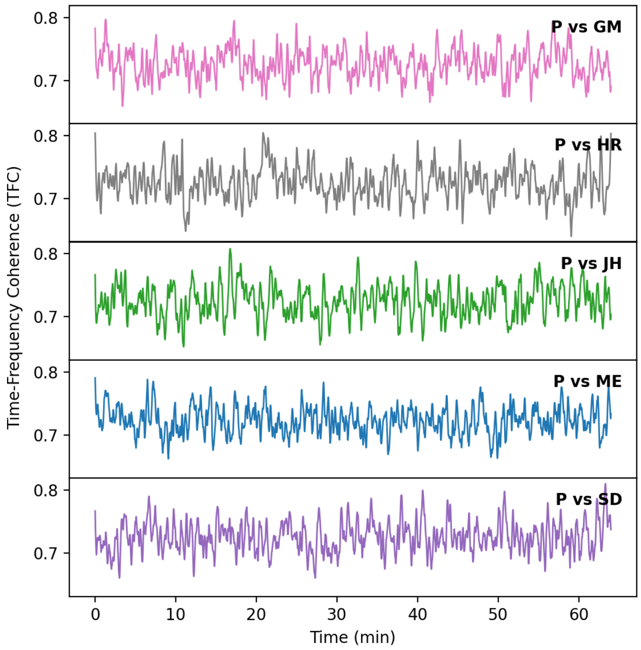

Figure 5: Time-frequency coherence, averaged over frequencies, between each patient-medical team member pair.

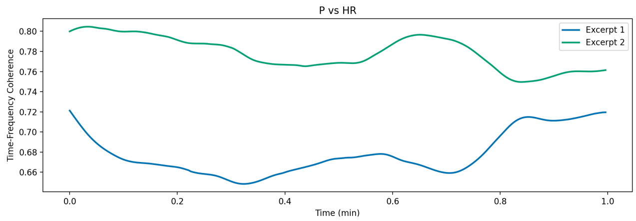

Figure 6: Two excerpts from patient versus team member HR used for sonification.

The following rule-based system was implemented to map distances between pitches in the spiral array for the patient versus medical team members based on average TFC values:

1. Pitches for the patient are randomly selected from a list of pitches provided by the user, using weighted random sampling.
2. For all team members:
3. For all heartbeats of the team member:
   (a) TFC values are selected only for sample points where a heartbeat occurs for the team member[6].
   (b) The closest heartbeat of the patient prior to the heartbeat of the medical team member is located. The pitch for this heartbeat is used as reference when computing distances in the spiral array.
   (c) If TFC identified in 3 (a) is below threshold A[7] (low coherence $<= 0.72$), select a dissonant interval[8], i.e. large distance in the spiral array.
   (d) If TFC is above threshold A (high coherence, $=> 0.72$ & $<= 0.77$), select a consonant interval[9], i.e. a small distance in the spiral array.
   (e) If TFC is higher than threshold B (> 0.77)[10], select no interval, i.e. the patient pitch equals the medical team member's pitch.

[6]This was done since the TFC values are available for a higher sampling rate than the heartbeat occurrence; heartbeats occur only as discrete events.

[7]The threshold was set to the average of the mean TFC for all persons.

[8]Dissonant distance in the spiral array was set to [2.0, 3.0].

[9]Consonant distance in the spiral array was set to [0.1, 2.0].

[10]97.5% of the smallest value among all maximum TFC values.

Person	Mean	Median	Min	Max	SD
P-GM	0.73	0.73	0.66	0.80	0.02
P-HR	0.72	0.72	0.64	0.80	0.03
P-JH	0.72	0.72	0.65	0.81	0.03
P-ME	0.72	0.72	0.66	0.79	0.02
P-SD	0.73	0.72	0.66	0.81	0.02

Table 2: Descriptive statistics of average TFC between patient (P) and medical team members.

The user can customize the input to the system in step 1. We used 1) a C Major pentatonic scale (which will always sound rather consonant), and 2) pitches from consonant bars (1 and 84) of *La Cathédrale Engloutie* by Claude Debussy. Step 5 (c) and (d) where further divided into smaller ranges with clearly defined distances in the spiral array, in order to give finer control of the selection of pitches within the harmonic versus dissonant range. The above described procedure outputs a set of pitches for the patient and respective person in the medical team, which can then be used for sound synthesis in SuperCollider. Each time the script is run, a new selection of pitches will be generated, according to the logic presented. In other words, the procedure can be repeated until you obtain a sonic result that you prefer. An example of a transcription generated from 10 heartbeats of all team members is displayed in Fig. 7.

Figure 7: Example output of the system, produced by 10 heartbeats of patient and medical team.

Since the spiral array takes pitch spellings into account, the distance between C and A♭ versus G♯ will be different (see Fig. 1). In our implementation, pitch spellings were not accounted for (the smallest distance was chosen, independently of pitch spelling). Maximum distance was set to the diminished fifth, since this is perceived as very dissonant. For example, if starting on a C, maximum distance was obtained for F♯. A full list of distances between pitches is available as supplementary material.

3.4. Sound Design and Sound Synthesis

Opted mapping scheme was designed with specific musical outcomes in mind, without compromising the presentation of the data in terms of accuracy. Sonifications in musical form, i.e. musifications, have been shown to facilitate deeper engagement with complex multidimensional data in previous biomedical applications [55]. Moreover, it has been shown that listeners participating in longer perceptual tests tend to find music less fatiguing than test tones, noise, or speech sounds [56].

Sound synthesis was done using SuperCollider. Mapping strategies are visualized in Fig. 8. As shown in this figure, the output of the sonification was a set of six voices (one per person). Heartbeats were used to trigger sounds for each person, and TFC was used to select pitches for the medical staff. In addition, we mapped TFC to the loudness of these sounds, so that increased coherence resulted in louder sounds for medical team members. The sound level of the patient was kept constant. With this as a starting point, we explored a range of different sound models. The ones included in this paper are synthesis of glockenspiel sounds, and

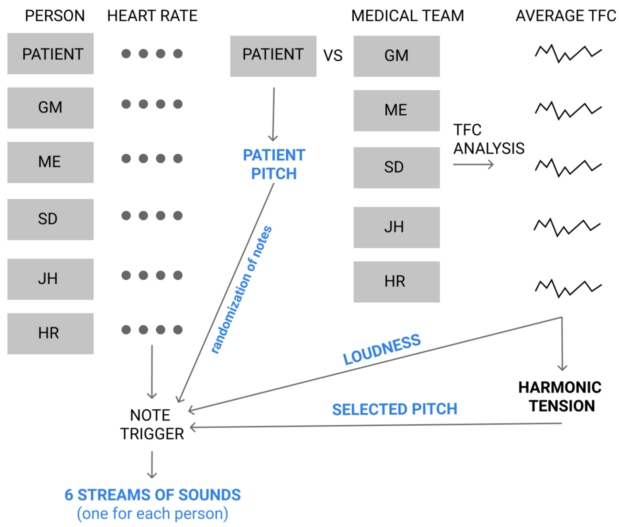

Figure 8: Mappings between heartbeat timing, average TFC and sounds.

sampling of pitch-shifted cello plucking sounds. For both of these models, a Schroeder reverb was also applied.

Sound examples of pairwise comparisons between patient and respective person in the medical team are available as supplementary material. We have also included examples in which all six voices, i.e. all persons in the medical team, are sonified simultaneously. Available sound examples include excerpts of the data when TFC is particularly low versus high, to highlight the sonic representation's ability to sonify differences in TFC.

3.5. Visualization

In order to further highlight the rhythmical structures created by all heartbeats as well as the differences between patient and medical team member's TFCs, we created a visualization of the voices using Processing. Communication between SuperCollider and Processing was enabled using OSC (Open Sound Control); thus allowing for direct mapping between heart signal properties and visual parameters, synchronized with outputted sounds. The visualization was designed in the form of a 2D space in which each person is represented by a colored square on a dedicated row, as seen in Fig. 9. The patient's square is displayed at the top, with medical team members' squares situated below him. For every heartbeat, the squares move a step to the right. Mean TFC between each person in the medical staff and the patient was mapped to a blue component of the color of the square; greater TFC resulted in a color more similar to that of the patient, which had a red hue. In

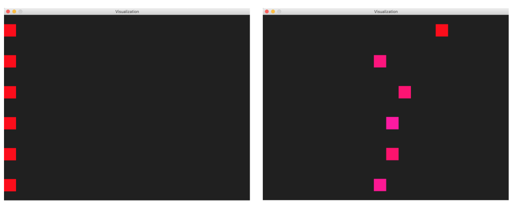

Figure 9: Visualization of the heartbeats and mean TFC for start position (left) and after some heartbeats (right). The patient is represented by the top square, which is ahead of the medical team (represented by squares situated below, and to the left of the patient, since their heart rates are slower.

this manner, the visualization not only highlights which heart rates that are synchronized, but also time-frequency coherence. Videos of the visualization are available as supplementary material.

4. EVALUATION

We conducted a web-based auditory-only listening experiment to evaluate if the proposed sonification framework could be used to successfully communicate TFC through sounds.

4.1. Participants

Participants were recruited on social media platforms and through mailing lists. The experiment was published using an online survey platform[11].

4.2. Stimuli

We created stimuli divided into two categories: *coherent* versus *non-coherent*. These two categories consisted of sound files created by data excerpts with an average TFC below[12] versus above[13] threshold A (see Sec. 3.3). We included 5 stimuli per category, with one excerpt for each medical team member versus patient pair. Sounds were created for both sound models, resulting in a total of 10 sound stimuli pairs (20 sound files in total). As input to the system, we provided the first bar of the Debussy piece. For this experiment, only the patient and one medical team member was sonified. Although loudness was originally used in the mapping described in Sec. 3.4, loudness level was kept constant in the experiment to avoid introducing a confounding variable. All sound files were normalized using the *perceived loudness normalization* function in Audacity.

4.3. Procedure

Participants were first presented with an introductory page describing the purpose of the study and whether they consented to their data being collected. They were then given the following instructions:

In this survey, you will be asked to listen to sounds created from heart signals of a COVID-19 patient and a doctor treating this patient. The sounds are sonifications[14]*, i.e. non-speech audio signals used to convey information. The sonifications will sound differently depending on if the spectral content of the heart signals of the patient versus the doctor are similar or not (how coherent the signals are). When the heart signals are coherent, the sound will be more consonant (i.e., not sound dissonant). When the heart signals of the patient and doctor are not coherent, the sound will be more dissonant. In this survey, your task is to listen to 2 sounds, and then select the sound that you think is generated by the most coherent heart signals. Please note that the sounds are directly mapped to heartbeat data. As a result, different sounds will have different rhythmic structures. Please don't consider the differences in rhythmical structure when deciding which of the two sounds that you think is coming from the most coherent signals.*

This was followed by a page with questions related to demographics (age, gender, nationality, country of residence, level of

[11] See `https://survey.alchemer.com/s3/6284149/Heartbeat-Sonification-Survey` and supplementary material.

[12] Average TFCs: [0.65, 0.66, 0.67, 0.70, 0.70], selected to represent all ranges used in 3 (c) of the framework presented in Sec. 3.3.

[13] Average TFCs: [0.72, 0.74, 0.76, 0.79, 0.80], selected to represent all ranges used in 3 (d) of the framework presented in Sec. 3.3.

[14] `https://sonification.de/son/definition/`

Stimulus	Glockenspiel	Cello
P-GM	78.05	78.05
P-HR	80.49	73.17
P-JH	58.54	53.66
P-ME	60.98	68.29
P-SD	68.29	68.29

Table 3: Accuracy (%) per sound model and stimuli pair.

musical expertise, and if they have had any formal musical training). Then, each page presented two sounds from the *coherent* versus *non-coherent* categories, both synthesized using the same sound model. Participants were asked to select the sound that they thought originated from the most coherent data. The task was repeated 10 times with different stimuli. The presentation order of the stimuli was randomized for each participant. Finally, participants could optionally leave a comment about the *aesthetics* and *usability* of the presented sounds, including aspects related to *pleasantness*, *informativeness* and long-term listening, terms selected based on measures used in previous research presented in [26].

4.4. Results

A total of 41 participants took part in the listening test (average age 45.95, 14 F, 27 M). In terms of musical expertise, 10 reported full-professional activity (experts), 8 semi-professional activity (several years of practice, skills confirmed), 8 some experience (advanced amateur, some years of practice), 9 little experience (occasional amateur), and 6 no experience. A total of 26 reported having had formal musical training. Pooling data across sound model and stimuli resulted in a total overall accuracy of 69.27%. A one-sample χ^2 test without continuity correction suggested that overall accuracy was above chance ($\chi^2(1, n = 410) = 57.84, p < 0.001$). Total accuracy per sound model when pooling data across stimuli was 69.27% for the glockenspiel model, and 68.29% for the cello model. Pooling across sound models resulted in total accuracy ranges from 56.10% (stimuli pair P-JH[15]) to 78.05% (P-GM[16]).

Results divided by stimuli and sound model are presented in Tab. 3. Poisson regression analysis was carried out to predict the number of correct replies based on musical experience, sound model, and stimulus pair. However, no significant effects were identified. Overall, accuracy measures ranged from 53.66% (stimulus pair P-JH using cello[17]) to 80.49% (stimulus pair P-HR using glockenspiel[18]).

In order to evaluate if musical experts versus non-experts differed in accuracy, we assigned data for persons identifying as musical experts or semi-professionals to one category, and persons not identifying as musical experts or semi-professional to another one. This resulted in one group of 18 experts, and 23 non-experts. Results are presented in Tab. 4. Pooling data across sound models and stimuli pairs, overall accuracy for experts was 71.11%. The corresponding percentage for non-experts was 66.96%. A χ^2 test revealed no significant difference in accuracy between the two groups.

Results from the open text question also provided some insights. For example, 5 participants commented on the *rhythmical structure* of the sounds. One participant mentioned that it was difficult to decouple the rhythmical structure when performing the task, and that rhythm also affected his overall perception of coherence and dissonance. Another participant stated: *"(...) it wasn't that easy to separate the rhythmic relation from the perceived coherence of the sounds. The various qualities of the sound work together forming the experience for me."* Yet a third participant described: *"The erratic rhythmic structure also influenced the way I perceived something to be consonant/dissonant."* In general, most comments about the sounds were positive. For example, 4 participants explicitly described the sonifications as *pleasant*. One participant mentioned that the glockenspiel sounds were perhaps a bit more pleasant, and that they portrayed dissonance more clearly. Regarding *informativeness*, one participant mentioned that the sounds were quite informative on the coherency, and 2 participants mentioned that it was easier to detect the more coherent signal after some practice. When it comes to *long-term listening*, one participant mentioned *"(...) the sounds are pleasant but they would start to blend-in with the background in a long-term listening session"*. In addition, 2 participants described that it was difficult to decide which sound to pick after listening to multiple stimuli.

[15]Average TFC values used to create these sonifications: 0.76, 0.66.
[16]Average TFC: 0.79, 0.70.
[17]Average TFC: 0.76, 0.66.
[18]Average TFC: 0.80, 0.65.

	P-GM	P-HR	P-JH	P-ME	P-SD	Exp.
Glockenspiel	77.79	72.22	66.67	77.78	77.78	E
	78.26	86.96	52.17	47.83	60.87	N
Cello	72.22	66.67	55.56	66.67	77.78	E
	82.61	78.26	52.17	69.57	60.87	N

Table 4: Accuracy per sound model (%) and stimuli pair for experts and semi-experts (E) versus non-experts (N).

5. DISCUSSION

The current work aimed to explore potentials of mapping time-frequency coherence between heart signals to musical parameters related to the notion of musical tension in sonifications of heartbeats in an offline setting. Based on the overall accuracy of 69.27%, we can conclude that the proposed framework was rather successful in terms of communicating coherence. Considering that the listening experiment was based on 10 second excerpts in which TFC varied over time, participants had to do some averaging in how they perceived the sounds. In other words, 100% accuracy is not to be expected.

Qualitative findings suggested that the rhythmical structure of the sonified heartbeats may influence how coherent sonifications are perceived. This tendency to be unable to decouple the rhythmical pattern is an interesting finding, considering that both temporal patterns and spectral aspects are of interest when sonifying heart signals. The finding motivates future studies focused on how temporal versus spectral properties of heart signals can be mapped to musical parameters.

Suggestions for future work building on the study presented in this paper involves speeding up the playback of the data to more easily portray larger changes over time, and to develop sound models that better fit such a representation. Additional work could also include exploring different mapping strategies, for example mappings between heart rates and octaves (resulting in higher frequencies if the heart rate speeds up, while maintaining the same pitch intervals). Finally, it would be interesting to explore how other measures of tension could be mapped across a moving window of heartbeats to create pitch clouds and chords, based on TFC.

6. CONCLUSIONS

In this paper we presented exploratory work focused on mapping time-frequency coherence measures of the heartbeats of a COVID-19 patient versus persons in a medical team to notions of harmonic tension in music. Results from a listening experiment suggests that the proposed framework was successful in the terms of communicating low versus high coherence through sonification.

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