MEASURING VIRTUAL AUDIENCES WITH THE MUSICLAB APP: PROOF OF CONCEPT

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ABSTRACT

We present a proof of concept by using the mobile application MusicLab to measure motion during a livestreamed concert and examining its relation to musical features. With the MusicLab App, participants' own smartphones' inertial measurement unit (IMU) sensors can be leveraged to record their motion and their subjective experiences collected through survey responses. The MusicLab Lockdown Rave was an Algorave (live-coded dance music) livestreamed concert featuring prolific performers Renick Bell and Khoparzi. They livestreamed for an international audience who wore their smartphones with the MusicLab App while they listened/danced to the performances. From their acceleration, we computed quantity of motion and compared it to musical features that have previously been associated with music-related motion, namely pulse clarity and low and high spectral flux. By encountering challenges and implementing improvements, the MusicLab App has become a useful tool for researching music-related motion.

1. INTRODUCTION

Virtual concert popularity increased as a result of the COVID-19 pandemic as musicians adapted to the social distancing requirements, and they livestreamed or recorded their performances for their audiences. However, how did this impact people's movement to music? It is generally known that music makes us move. Certain genres such as dance music make us move more even when we try to stand still [1]. Musical features, such as the "drop" in electronic dance music [2], or pulse clarity and low frequency spectral flux in popular music [3], evoke more movement from listeners. Furthermore, personal characteristics such as emotion [4], personality [5]–[7], and fan-status [8], and environmental factors such as social context [7] and liveness [8] influence music-related motion.

Movement is an important component of engagement with music because it not only influences the way that we enjoy music [9], but also the way that music is perceived [10]. While conventional music cognition may

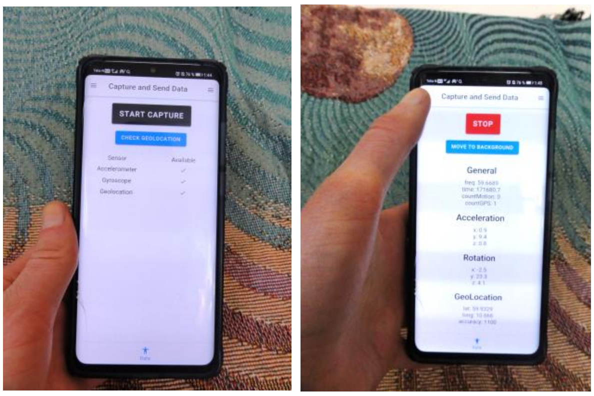

Figure 1: The MusicLab App is a mobile application that can be installed on participants' own smartphones.

consider action and perception as distinct, research from neuroscience, psychology and behaviour indicate that perception and action are tightly linked. For example, when participants moved to a rhythm with an ambiguous meter every two or three beats, they perceived the meter as being duple or triple, respectively [11]. Movement can assist with musical timing perception [12]. Even when participants are instructed to simply imagine accented beats, this imagined meter is encoded in their brain signals as it would be if they had really heard the meter [13]. Embodied music cognition unites action and perception in a framework that situates the body at the centre of musical interaction [14], [15].

Another important component of musical experience is its social nature. Music is a social phenomenon because performing and listening typically occur in the presence of others [16]. Even solitary music listening can be considered social because there is an imagined presence of the musicians. A concert is typically a very social experience in which artists and audience share time and space. A virtual concert may be viewed as a livestream (shared time) or pre-recorded. Livestreamed concerts are unique social contexts where audience members may be listening physically alone, but interacting online with other audience members and experiencing the concert at the same time. People may move differently depending on whether they are with others (e.g. move more as they dancing together or move less to fit in with social norms), or if they are alone (e.g. move more due to shyness or move less because they don't have others to communicate with). Embodied music cognition can support research into the social elements of music cognition as long as the social nature of music is also considered when designing and interpreting research findings [17].

Motion can be measured with a variety of tools ranging in features including cost, portability, and precision. Optical motion capture systems record motion in 3 dimensions using cameras that emit and capture infrared light from reflective markers attached to participants. They are costly and often require a dedicated lab space, however the data has very high precision [18]. Video can measure motion for relatively low cost and with excellent portability, however it lacks the high-precision offered by the state-of-the art optical motion capture systems. Inertial measurement unit (IMU) sensors consist of an accelerometer, gyroscope, and magnetometer which measure acceleration, orientation, and geolocation, respectively. They are portable (present in most smartphones and can also be purchased separately) and are low-cost. Position measured from geolocation is low precision compared to video and optical motion capture systems, however IMU sensors measure acceleration at a high precision. Data privacy concerns are greater with video, audio, and motion capture data as IMU sensors do not record pictures of faces. Nonetheless, geolocation could reveal a participant's identity which is why there are several protocols for obscuring location data prior to publication [19]. A comparison between inertial sensors, video, and optical motion capture in a single group dance experiment highlighted that each measurement technique has its own strengths and weaknesses and combining systems is helpful for understanding motion [20].

The MusicLab App is a smartphone application available for both Android and Apple operating systems that collects motion from participants' own smartphone IMU sensors. The application can also collect survey responses through a connection with the University of Oslo's webform system. In accordance with current privacy regulations (specifically, the GDPR), both motion and survey responses are stored in secure servers at the University of Oslo (using the Nettskjema service). The app's source code is freely available and is in continuous development[1]. It was developed to be used in conjunction with MusicLab events, which feature a combination of a musical performance, a research component, a panel discussion, and "DJ"ing in the form of "Data Jockeying", in which a researcher demonstrates how the data that was collected will be analysed. These events aim to embody the principles of open science and FAIR data while managing copyright and privacy concerns [21].

In the summer of 2020, live-coding performers Renick Bell and Khoparzi livestreamed Algorave (live-coded dance) music for an international virtual audience[2]. The live-coded music was improvised and varied in pulse clarity with some sections being more danceable with a clear beat and others having a less clear pulse. Participants used the MusicLab App to measure their motion and respond to questionnaires. Motion and musical features were extracted and compared to understand their relations in a virtual concert. All music, code, and anonymized data was published under a CC-by 4.0 license and can be accessed at the OSF repository[3]. The main aim of this study was to provide a proof of concept for using the MusicLab App at a livestreamed concert.

2. METHODS

Participants were recruited and the concert was promoted through targeted Facebook advertising and performers' social networks.

2.1 Technical Set-up

The event host was situated in Finland so she joined a Zoom video call that was livestreamed into YouTube by the first author in Norway via Open Broadcaster Software (OBS). The YouTube stream key was sent to the first performer who livestreamed from Japan and then to the second performer who livestreamed from India. After the performances, the performers and researchers gathered on Zoom for a panel discussion. Following the panel discussion, a preliminary data analysis was live-coded to reveal to the audience how their data can be used (code: https://github.com/fourMs/MusicLab5).

2.2 Participant Instructions

Participants were instructed to download the MusicLab app provided in links in the video description. Participants provided consent in the MusicLab app in accordance with the Declaration of Helsinki, 2013. The Norwegian Centre for Research Data approved the study (741882).

Moderators provided technical support by responding to questions in the YouTube live chat. Participants were encouraged to place their phones on their upper bodies (such as in a shirt chest pocket) and to stand for the duration of the concert. They were told to dance if they felt the desire to do so.

Before the concert, participants responded to a survey in the MusicLab App that collected demographic information (age, gender, nationality), musical information (musician status, experience with Algorave and livestreams, fan-status), sensorimotor and social components of the Barcelona Musical Reward Questionnaire [22], the ten-item personality inventory [23], and the empathic concern and fantasy subscales of the interpersonal reactivity index [24]. After each performance they responded to questions on the performance (its danceability, familiarity, enjoyment, audio and video quality), motion (phone location, amount of their own motion to the beat and the performer's motion to the beat), social experience (connectedness to the performer and other audience members, perceived performer interaction with the audience, and whether there was anyone watching the performance with them), and their personal state (level of attention and amount of standing or sitting).

[1] https://github.com/fourMs/MoMoCapture

[2] Watch their performance here: https://youtu.be/hJ73IGYawuM

[3] OSF Repository DOI: 10.17605/OSF.IO/7J2GA

2.3 Alignment

To enable aligning the motion signals with the music, participants were instructed to begin recording while their phone was on a flat surface and to shake their phones twice when they heard the first sound from each performer. Preliminary testing indicated that this shake would be easily identifiable in the motion signal.

The accelerometer data was visually inspected during the two minutes that followed the start of the first sound from each performer. The first indication of a shake was presumed to be the shake. (There were a few participants that had several shake-like features in close proximity to the start of the song.) Since participants picked up their phones and then shook them at the first sound they heard, the initiation of the shake was manually selected as the start of the performance. Performance duration was used to demarcate the end of the performance.

2.4 Motion Features

Acceleration had average sampling rates near 60 Hz. However, this was variable between devices and also within some devices.

Acceleration signals were low-passed filtered with a Butterworth filter with a cutoff at 5 Hz to focus on meaningful human motion. The filtered acceleration was then downsampled to 10 Hz. The quantity of motion time series (QoM) was calculated as in equation (1) for the duration of the performance, taking the absolute change of the accelerometer data per sample to represent when participants were moving to the music [25].

$$\boldsymbol{QoM} = \sqrt{(\boldsymbol{x_{t2}} - \boldsymbol{x_{t1}})^2 + (\boldsymbol{y_{t2}} - \boldsymbol{y_{t1}})^2 + (\boldsymbol{z_{t2}} - \boldsymbol{z_{t1}})^2} \quad (1)$$

The resulting QoM data was smoothed using a Savitzky-Golay filter (order: 1, window: 299).

2.5 Musical Features

Musical recordings were trimmed in REAPER to remove silence from the beginning and end. Musical features were extracted using the MIRtoolbox for MATLAB (2019) [26]. We chose to analyze only musical features that have previously been related with motion: pulse clarity, and low and high-frequency spectral flux [3], [27], [28]. Pulse clarity estimates how clear the beat of the music is [30], and was computed using frame decomposition with the default values for window length (5 s) and hop length (500 ms). Spectral flux quantifies the amount that the frequency spectrum of a signal changes over time. The sub-band flux was computed by splitting it into 10 bands of 1 octave each, and using the frame decomposition method as in Alluri and Toiviainen comparing consecutive frames with a window length of 25 ms half overlapping (i.e. hop length of 12.5 ms) [30]. Low-frequency spectral flux has previously been related to greater speed of head movement [27] and more entrainment to the beat and bar levels of the musical rhythms [3]. In accordance with previous literature, low-frequency spectral flux was defined by the frequency ranges 50–100 Hz (sub-band no. 2; [27]) and 100–200 Hz (sub-band no. 3; [28]). We chose to examine both sub-bands of low-frequency spectral flux to ensure we captured any existing relations between these musical features and the motion. High-frequency spectral flux was defined as the range 6400–12800 Hz (sub-band no. 9) and has previously been related to greater speed of head and hand movement and amount of movement [27]. This sub-band flux represents rhythmic information in sounds resembling cymbals and hi-hats.

2.6 Analysis

QoM and musical features were compared using Spearman correlations. To compare these measures, both time series were resampled to 2 Hz. Time series were trimmed to remove the first 30-seconds. Spearman correlations were conducted for each point in the time series. Several participants had data loss events and rather than filling these motion gaps when resampling, any gaps in the original signal that were greater than 1 second were removed from the analysis.

3. RESULTS

3.1 Participants

Due to issues with the versions of the app at the time, there were several data loss events and challenges, especially with the Apple version of the application. In particular, Apple does not permit background recording, and therefore there are gaps in the data if the screen turns off or if the user navigates away from the MusicLab App. Certain Android phones also have battery optimization procedures that prevent background recording unless an application is given permission.

Figure 2: Geolocation data was collected from 14 participants

There were 7 participants with accelerometer data during Renick Bell's performance. Exclusion criteria included alignment issues, unrealistic human motion (complete stillness), and other data issues. One of the participants began recording after the start of the performance therefore a shake was not measured within an appropriate timeframe. Another participant had a shake that was much later than the other participants. Since this makes the alignment questionable, we excluded them for this analysis. Therefore, the sample size of Renick Bell's audience is n = 5 for this analysis. Of these participants, n = 4 filled the pre-concert survey and the post-performance survey for Renick. Due to the small sample sizes, this paper should be interpreted as a proof of concept and no conclusions on the relation between motion and musical features can be drawn.

There were 7 participants with accelerometer data during Khoparzi's performance. One of the participants had a sampling frequency of 9 Hz on average, which is much lower than the other participants and it appeared as though the phone was static as if it wasn't secured to a body, therefore this participant was excluded. Another participant had three shakes in very close proximity. Since it was challenging to guarantee proper alignment, this participant was excluded. Another participant had only 4 minutes of data. Therefore, the final sample size of Khoparzi's audience is n = 4 for this analysis. Of these participants, all 4 filled the pre-concert survey and the post-performance survey for Khoparzi. Two participants had data during both Renick's and Khoparzi's performances.

3.2 Alignment Method Assessment

The alignment method could be improved. Due to the nature of the signal, the solution that worked best for identifying the shake was visual inspection. Automating alignment could improve the functionality of the MusicLab app, especially if there was a larger amount of data.

3.3 Music-related Motion

Correlations were conducted on each individual for illustrative purposes. Due to the small sample size, results should be interpreted with caution and should simply serve as a proof of concept. The correlations between quantity of motion and audio features are generally very low.

Renick	**PC**	**Low**	**Low 2**	**High**
1	-0.024	0.067	0.034	-0.019
2	-0.0082	0.013	-0.023	0.049
3	0.1	0.17	0.13	0.14
4	-0.031	-0.018	-0.019	-0.026
5	-0.048	-0.067	-0.055	0.016
Khoparzi	**PC**	**Low**	**Low 2**	**High**
2	0.18	0.042	0.092	0.11
4	0.098	0.024	0.038	0.13
6	0.07	0.048	0.066	-0.022
7	-0.13	-0.12	-0.11	0.097

Table 1: Correlations between quantity of motion and musical features

3.3.1 Pulse Clarity

In Renick's audience, one participant demonstrated a positive correlation between quantity of motion and pulse clarity. Interestingly, this participant reported that he enjoyed the performance more than all other participants (level of 6 out of 7; average level of enjoyment of other participants: 4), but he did not feel like he was moving to the beat (2/7).

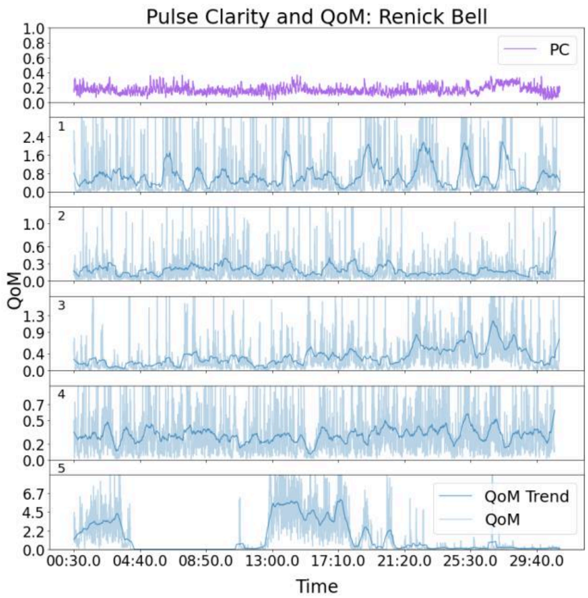

Figure 3: Pulse clarity and quantity of motion for each participant (1, 2, 3, 4, and 5), during Renick Bell's performance. Note that the y-axis is scaled to 1.5 x the maximum QoM trend for each participant and that some QoM peaks are cut off by the scaling. This scaling allows visualization of the variability within a single participant, but refer to the y-axis for the variability between participants.

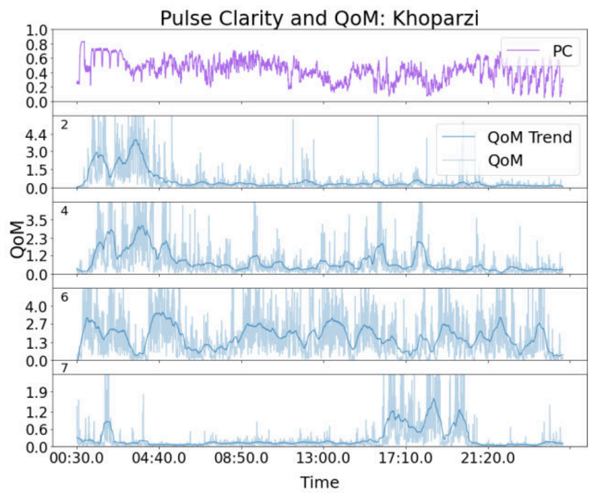

Figure 4: Pulse clarity and quantity of motion for each participant (2, 4, 6, and 7) during Khoparzi's performance. Note that the y-axis is scaled to 1.5 x the maximum QoM trend for each participant and that some QoM peaks are cut off by the scaling. This scaling allows visualization of the variability within a single participant, but refer to the y-axis for the variability between participants.

In Khoparzi's audience, three participants demonstrated a positive correlation between quantity of motion and pulse clarity, however one participant had a negative correlation. When visually inspecting this participant's motion, it appears that they were very still for most of the performance but moved around the middle of the performance. Unfortunately, there is no post-performance questionnaire for the participant therefore we are unable to investigate if this participant could have been sitting in the first half of the concert.

Spectral flux

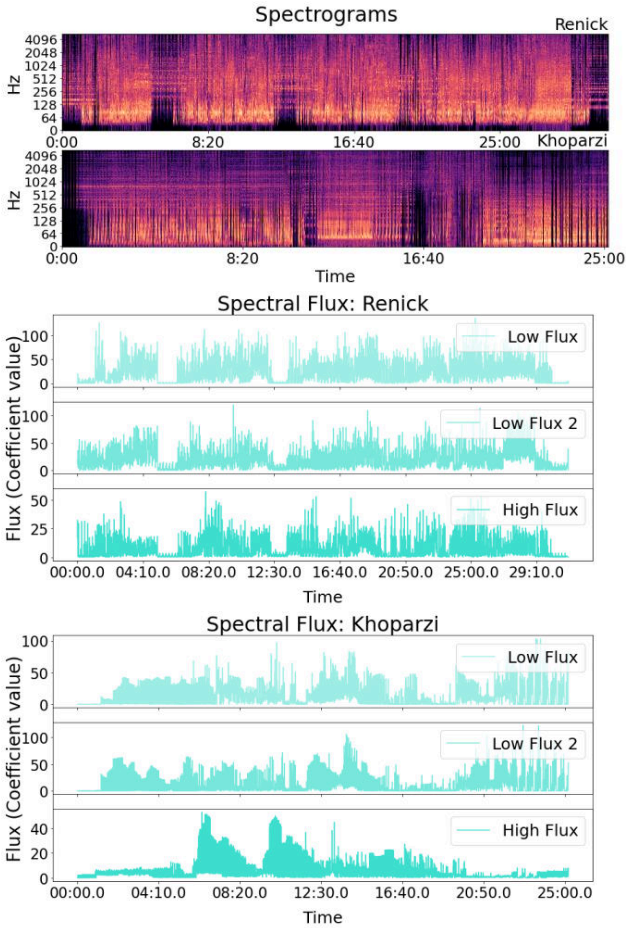

Figure 5: Spectrograms of each audio clip and spectral flux in low and high frequency flux bands for Renick and Khoparzi's performances. Note that for spectral flux, the y-axis is scaled to each sub-band, so refer to the y-axes for the variability between performers.

In Renick's audience, two participants demonstrated a positive correlation between QoM and low frequency spectral flux. The participant that showed the positive correlation with pulse clarity is the same with the strongest correlation in the low frequency sub-band. In the higher low frequency sub-band (band no. 3), this same participant has the strongest correlation again. For high frequency spectral flux, there were two participants with positive correlations, the same participant as before and another participant that did not show correlations in the low frequency flux.

In Khoparzi's audience, one audience member showed a negative correlation between QoM and low frequency flux (band no. 2). In the higher low frequency flux, two participants demonstrated positive correlations and the same participant as before demonstrated a negative correlation.

Khoparzi had a higher level of pulse clarity than Renick. The differences in pulse clarity are also easily heard in the audio, where there are more irregular rhythms during Renick's performance. Renick performed with more spectral flux in all frequency bands. In addition to the performances being quantitatively different, they were qualitatively different featuring different timbres rhythmic components, and coding/musical styles.

3.4 Shared Location

Through data exploration, it was observed that two individuals (participants 2 and 4) had the same geolocation and they indeed reported that they were watching the performance together with another person. They both had motion data during Khoparzi's performance therefore we calculated a Pearson correlation between their quantity of motion (r = .26). The other participants' quantity of motion were much less correlated (r ranging from -.08 to .01). A visual inspection of the motion indicated that it may be that one of their motion datasets was misaligned because shifting one later by 17 seconds aligned the signals even better for a Pearson correlation of r = .43.

Figure 5: Two participants watched the concert together and showed high correlation between their quantity of motion. The trends are displayed here normalized for each participant. However, the correlation was improved by shifting the data in time which may indicate that the alignment method could be improved in future research.

It appears that the participant indicated in blue may have begun recording too late and thus shook their phone too late such that the first sound actually happened before the participant began recording. This further indicates that the alignment method used for this experiment was flawed and taking care to ensure that participants are warned well in advance of when to begin their motion recording should prevent situations like this.

4. DISCUSSION

The MusicLab Lockdown Rave concert experiment served as a proof of concept showing that remote motion measurement is indeed a useful way of measuring music-induced motion. Accelerometer data collected from the inertial measurement units of participants' own smartphones can be converted into quantity of motion data and subsequently compared to musical features, or to other individuals' movement.

The analysis presented here indicates two important components of working with these types of applications. The alignment method conducted for this experiment proved to be challenging to automate during analysis. It is also prone to participant error since it relied on participants reacting quickly to a sound. One solution would be to simultaneously record audio from the participants' own smartphones. While an audio synchronization might be convenient, privacy concerns, technical complications, and app distributor constraints render this an untenable strategy at this time.

Through trying to solve this alignment challenge, we developed a new strategy in which participants tap on their smartphones to a recording of an isochronous beat at two distinct tempi. Our testing shows that the tap of a finger on the phone produces sufficient acceleration to be detected in the signal. However, due to participant errors when tapping, such a method still requires some visual inspection to ensure that alignment occurs properly.

Previous research indicated that movement can be influenced by musical features including pulse clarity and high and low spectral flux, with more flux and pulse clarity leading to greater quantity of motion [3].The differences between the results presented here and the existing literature could be attributed to several factors including differences in the variability of pulse clarity in the stimuli. The live-coded algorave music that was improvised at this concert was a different genre than previously explored. Each performer used a distinct system for creating their music and the differences in sonic texture and rhythmicity between them and from music that has typically been examined in relation to music-induced motion may explain the observed differences.

In previous research participants' motion was measured in a laboratory context which offers more experimental control than measuring motion in participants' homes. Despite experimenter instructions and participants' best intentions, participants may be distracted from their task due to various interruptions that occur regularly in home life.

Virtual concerts are also very different experiences than live concerts due to differences in social and environmental factors. Due to social distancing guidelines, people may be watching virtual concerts alone rather than in groups and this would create a different propensity for movement. Research suggests that perceiving movement activates the same regions of the brain that are involved in producing the movement [31]. Therefore, if we are in the presence of others and perceiving others' actions, we may be more likely to move as well.

The social element of music listening, even during virtual concerts was shown by comparing two individuals who shared the concert experience together. The similarity between their quantity of motion may be indicative of similar movements. Given that motor entrainment promotes prosocial benefits [32], even when the entrainment occurs in virtual reality [33], it is possible that sharing virtual concert experiences could promote bonding, especially during times of social distancing. Indeed research supports that viewing livestreamed, but not pre-recorded virtual concerts promotes social connectedness and alleviates feelings of loneliness [34], [35]. Whether movement plays a role in feelings of togetherness at a virtual concert remains unexplored, however the MusicLab App is a useful tool for examining movement remotely.

After the MusicLab Algorave project, development on the application and the protocols associated with data collection continued based on the issues that arose. Rather than a pre- and post-concert survey, now up to 13 surveys can be administered at the same event. To reduce data loss during events, we have implemented a function so that data is submitted as 1-minute packages. In new app versions, surveys and motion data are also linked more reliably. Participants can withdraw their participation directly in the App. There are still some limitations including not being able to record motion in the background on all Apple and some Android devices. However, we implemented a screen dimming functionality that reduces screen brightness when data is being recorded. This feature will not only help prolong battery life, but it will also help make screens less disturbing to concertgoers.

Future applications of the MusicLab App include usage at live, hybrid, and virtual musical events, examination of coordination between audience members, and further exploration in different musical and ecologically valid contexts. The motion could also undergo more elaborate analyses than quantity of motion including periodicity or frequency-based analyses.

As a result of the improvements that were implemented through challenges discovered during the MusicLab Algorave project, the MusicLab App was ready for the next project. MusicLab Copenhagen was a large concert in which the Danish String Quartet performed to live and livestreaming audiences. There we successfully captured data from 79 participants in the live audience and 34 participants in the virtual audience. Adjustable phone holders were purchased so that the phones could sit high on wearers' chests, which provided a uniform position for recording across the live audience. Surveys were provided in the app in both English and Danish for livestreaming viewers to choose their preferred language. The MusicLab App has already proved itself a formidable tool for measuring motion remotely at virtual concerts and together in a live concert hall.

5. CONCLUSIONS

The MusicLab App is a mobile application developed to measure motion and collect surveys in musical audiences, who may be viewing a live concert together, or a virtual concert apart. It leverages the inertial measurement unit (IMU) sensor to track acceleration, rotation, and geolocation. Audience motion and survey responses can effectively be collected and used to understand how participants engage with and experience virtual concerts. The MusicLab App has undergone a number of improvements and has proved itself as a viable tool in the embodied music cognition researcher's toolkit.

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6. REFERENCES

[1] V. E. Gonzalez-sanchez, A. Zelechowska, and A. R. Jensenius, "Correspondences Between Music and Involuntary Human Micromotion During Standstill," *Front. Psychol.*, vol. 9, no. 1382, pp. 1–10, 2018.

[2] R. T. Solberg and A. R. Jensenius, "Group behaviour and interpersonal synchronization to electronic dance music," *Music. Sci.*, vol. 23, no. 1, pp. 111–134, 2019.

[3] B. Burger, M. R. Thompson, G. Luck, S. H. Saarikallio, and P. Toiviainen, "Hunting for the beat in the body: on period and phase locking in music-induced movement," *Front. Hum. Neurosci.*, vol. 8, no. November, pp. 1–16, 2014.

[4] B. Burger, S. H. Saarikallio, G. Luck, M. R. Thompson, and P. Toiviainen, "Emotions Move Us : Basic Emotions in Music Influence People ' s Movement to Music," *Proc. 12th Int. Conf. Music Percept. Cogn. 8th Trienn. Conf. Eur. Soc. Cogn. Sci. Music*, no. November 2014, pp. 177–182, 2012.

[5] A. Zelechowska, V. E. G. Sanchez, B. Laeng, J. K. Vuoskoski, and A. R. Jensenius, "Who Moves to Music ? Empathic Concern Predicts Spontaneous Movement Responses to Rhythm and Music," vol. 3, pp. 1–16, 2020.

[6] E. Carlson, B. Burger, J. London, M. R. Thompson, and P. Toiviainen, "Conscientiousness and Extraversion relate to responsiveness to tempo in dance," *Hum. Mov. Sci.*, vol. 49, pp. 315–325, 2016.

[7] E. Carlson, B. Burger, and P. Toiviainen, "Dance Like Someone is Watching: A Social Relations Model Study of Music-Induced Movement," *Music Sci.*, vol. 1, p. 205920431880784, 2018.

[8] D. Swarbrick *et al.*, "How live music moves us: Head movement differences in audiences to live versus recorded music," *Front. Psychol.*, vol. 9, no. 2682, pp. 1–11, 2019.

[9] P. Janata, S. T. Tomic, and J. M. Haberman, "Sensorimotor Coupling in Music and the Psychology of the Groove," *J. Exp. Psychol. Gen.*, vol. 141, no. 1, pp. 54–75, 2011.

[10] P. J. Maes, M. Leman, C. Palmer, and M. M. Wanderley, "Action-based effects on music perception," *Front. Psychol.*, vol. 4, no. JAN, pp. 1–14, 2014.

[11] J. Phillips-silver and L. J. Trainor, "Hearing what the body feels : Auditory encoding of rhythmic movement," vol. 105, pp. 533–546, 2007.

[12] F. Manning and M. Schutz, "' Moving to the beat ' improves timing perception," pp. 1133–1139, 2013.

[13] S. Nozaradan, I. Peretz, M. Missal, and A. Mouraux, "Tagging the Neuronal Entrainment to Beat and Meter," *J. Neurosci.*, vol. 31, no. 28, pp. 10234–10240, 2011.

[14] M. Leman, P.-J. Maes, L. Nijs, and E. Van Dyck, "Embodied Music Cognition," in *Springer Handbook of Systematic Musicology*, R. Bader, Ed. Springer, 2018.

[15] M. Leman, *Embodied music cognition and mediation technology*. MIT Press, 2008.

[16] I. Cross, "Music and social being," *Musicol. Aust.*, vol. 28, no. 1, pp. 114–126, 2005.

[17] N. Moran, "Social implications arise in embodied music cognition research which can counter musicological 'individualism,'" *Front. Psychol.*, vol. 5, no. JUL, pp. 1–10, 2014.

[18] A. R. Jensenius, "Methods for Studying Music-Related Body Motion," *Springer Handbooks*, pp. 805–818, 2018.

[19] K. H. Hampton *et al.*, "Mapping health data: Improved privacy protection with donut method geomasking," *Am. J. Epidemiol.*, vol. 172, no. 9, pp. 1062–1069, 2010.

[20] R. T. Solberg and A. R. Jensenius, "Optical or inertial? Evaluation of two motion capture systems for studies of dancing to electronic dance music," in *SMC 2016*, 2016.

[21] A. R. Jensenius, "Best versus Good Enough Practices for Open Music Research," *Empir.*

Musicol. Rev., vol. 16, no. 1, pp. 5–15, 2021.

[22] E. Mas-Herrero, J. Marco-Pallares, U. Lorenzo-Seva, R. J. Zatorre, and A. Rodriguez-Fornells, "Individual Differences in Music Reward Experiences," *Music Percept.*, vol. 31, no. 2, pp. 118–138, Dec. 2013.

[23] S. D. Gosling, P. J. Rentfrow, and W. B. Swann, "A very brief measure of the Big-Five personality domains," *J. Res. Pers.*, vol. 37, no. 6, pp. 504–528, 2003.

[24] M. H. Davis, "A Mulitdimensional Approach to Individual Differences in Empathy," *Cat. Sel. Doc. Psychol.*, vol. 10, no. MS. 2124, p. 85, 1980.

[25] T. Kelkar and A. R. Jensenius, "Analyzing free-hand sound-tracings of melodic phrases," *Appl. Sci.*, vol. 8, no. 1, 2018.

[26] O. Lartillot and P. Toiviainen, "A MATLAB toolbox for musical feature extraction from audio," in *Proceedings of the 10th International Conference on Music Information Retrieval, ISMIR 2007*, 2007, pp. 127–130.

[27] B. Burger, M. R. Thompson, G. Luck, S. Saarikallio, and P. Toiviainen, "Influences of Rhythm- and Timbre-Related Musical Features on Characteristics of Music-Induced Movement," *Front. Psychol.*, vol. 4, no. 183, 2013.

[28] B. Burger, J. London, M. R. Thompson, and P. Toiviainen, "Synchronization to metrical levels in music depends on low-frequency spectral components and tempo," *Psychol. Res.*, vol. 82, no. 6, pp. 1195–1211, 2018.

[29] O. Lartillot, T. Eerola, P. Toiviainen, and J. Fornari, "Multi-feature modeling of pulse clarity: Design, validation and optimization," *ISMIR 2008 - 9th Int. Conf. Music Inf. Retr.*, pp. 521–526, 2008.

[30] V. Alluri and P. Toiviainen, "Exploring perceptual and acoustical correlates of poly-phonic timbre," *Music Percept.*, vol. 27, no. 3, pp. 223–242, 2010.

[31] V. Gallese, L. Fadiga, L. Fogassi, and G. Rizzolatti, "Action recognition in the premotor cortex.," *Brain*, vol. 119 (Pt 2), pp. 593–609, Apr. 1996.

[32] L. Cross, M. Turgeon, and G. Atherton, "How Moving Together Binds Us Together: The Social Consequences of Interpersonal Entrainment and Group Processes," *Open Psychol.*, vol. 1, no. 1, pp. 273–302, 2019.

[33] B. Tarr, M. Slater, and E. Cohen, "Synchrony and social connection in immersive Virtual Reality," *Sci. Rep.*, vol. 8, no. 1, pp. 1–8, 2018.

[34] D. Swarbrick, B. Seibt, N. Grinspun, and J. K. Vuoskoski, "Corona Concerts: The Effect of Virtual Concert Characteristics on Social Connection and Kama Muta," *Front. Psychol.*, vol. 12, no. June, pp. 1–21, 2021.

[35] K. E. Onderdijk *et al.*, "Livestream Experiments: The Role of COVID-19, Agency, Presence, and Social Context in Facilitating Social Connectedness," *Front. Psychol.*, vol. 12, no. May, pp. 1–25, 2021.