Towards Developing a Virtual Guitar Instructor through Biometrics Informed Human-Computer Interaction

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Fig. 1. Capturing guitar performance information via our developed multimodal system, operating across two networked computers (accommodating two Myo wearable sensors, a microphone and a video camera).

Within the last few years, wearable sensor technologies have allowed us to access novel biometrics that give us the ability to connect musical gesture to computing systems. Doing this affords us to study how we perform musically and understand the process at data level. However, biometric information is complex and cannot be directly mapped to digital systems. In this work, we study how guitar performance techniques can be captured/analysed towards developing an AI which can provide real-time feedback to guitar students. We do this by performing musical exercises on the guitar whilst acquiring and processing biometric (plus audiovisual) information during their performance. Our results show: there are notable differences within biometrics when playing a guitar scale in two different ways (legato and staccato) and this outcome can be used to motivate our intention to build an AI guitar tutor.

CCS Concepts: • **Human-centered computing → Gestural input**.

Additional Key Words and Phrases: Deep learning, Biometrics, Musical performance, Guitar, Multimodal data, Game engines, EMG, HCI

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1 INTRODUCTION

This work uses wearable interfaces (Myo armbands) offering novel electromyographic (EMG) biometric information (measuring muscular amplitude/strength) to investigate how performance techniques are represented on the acoustic guitar instrument, via set musical exercises (scales), towards our goal: building an accessible artificial intelligence (AI) guitar instructor. These exercises are informed by exam board requirements in the UK [1, 17, 28], outlined in Table 1, for grade one guitar (beginner level–providing an initial focus for the work). EMG data is particularly useful within music performance research because it gives us the ability to understand nuanced performance behaviours and techniques. When paired with audiovisual information (taken from cameras and microphones, typically tracking performer movement and note frequency information), this provides a rich dataset for the extraction of meaningful performance features in musical research. The research questions we posit are: how is musical technique represented via EMG data? Is there a difference at data level between unique techniques on the guitar instrument? Our contribution in this work is an innovative method for acquiring and processing EMG biometrics for guitar performance, which allows the scientific and artistic communities to create instrument-specific feedback tools (noted to be an important topic and application based off prior related research [10]); ultimately increasing accessibility for music instrument education in the UK.

Modern wearable technologies are providing us with increased access to digital information, which describe our human behaviours, with applications ranging from monitoring exercise and fitness levels [4] to health [21]. Wearables, such as the Myo armbands by Thalmic Labs (now North), give us biometric information in the form of orientation and EMG data. The latter is particularly interesting for music and human-computer interaction (HCI) research because EMG data gives us an insight in to information found when performing with musical instruments, such as when using different, nuanced, performance techniques (e.g., performing with fingers or a plectrum, or playing staccato (detached) vs legato (smoothly)). These techniques develop as part of a musician's technical vocabulary and require time and practice to learn. They can be learnt as part of musical technical exercises (e.g., scales) or as part of musical phrases (riffs). Understanding how musical technique is formed is important to investigate because it allows us to pair musical intent and creativity with digital systems, giving us access to novel compositional and performative methods, as well as the potential for evaluative insights regarding performance strength.

However, EMG data is complex and signal processing methods must be used in order to deconstruct its complexity. Feature extraction must be used with EMG data in order to extract the most important and prominent features of the data, depending on the use case. Machine learning (ML) is also useful in this domain because it allows us to pair complex EMG information (representing musical gesture and performance) with interactive systems, such as game engines (as investigated during our earlier research [7, 8, 27]). Game engines offer unique opportunities for musical expression due to their developed physics engines and interactive/immersive features. However, game engines also offer novel ways of communicating complex information (e.g., visualisation) and simulating real world situations for training/education applications [3, 22]. Therefore, pairing such wearable interfaces with game engines allows us to investigate how musical technique can be communicated intuitively to student musicians (here, guitarists), which is the overarching goal and intended future path for this research enquiry.

This work is motivated by similar literature in the field, which investigates the classification of gestural information for musical instrument performance [9, 10, 30], towards understanding applications for doing so. The problems existing in the domain of musical performance and HCI concern methodologies and best practices for processing novel and more complex biometric information, such as EMG. Authors have successfully used deep learning models to classify orientation data, in partnership with professional musicians, but EMG information has seldom been used with deep learning algorithms [10]. Other authors have classified EMG biometrics with general ML algorithms towards creating a guitar which can be played in the 'air', where the problems outlined are the accuracy of the predictions and determining the sample size [30].

A range of instruments have also not been investigated, regarding the generalisability of the deep learning models.

Apart from the discussed scientific motivations, this work is also motivated by current research in the UK which shows that there is an emerging social problem regarding access to musical instrument education. In 2018, a UK report from the Musician's Union [6] warned that poorer children are less likely to be able to afford a music education (being "priced out"). In the same year, another UK report from the Royal Philharmonic Orchestra [20] found that most young people polled wanted to learn an instrument; the guitar was the most popular choice, showing uneven social access to music education but a collective desire for guitar education. In recent times, the COVID-19 pandemic has also changed the way people learn musical instruments. In 2021, the online music learning community saw a surge in revenue (projected $143 million by 2025) [33]. Therefore, as technology becomes more important for music education, there is potential for video games (via game engines) to be useful for studying guitar, albeit limited by individualised teacher feedback [29]. Within the technology industry, Apple and Facebook were recently granted patents for using biometrics within wearable technologies towards individualised feedback outside of music [23, 24]. In this work, we build on our previous research which classified musical gestures using EMG data from Myo armbands and compared the classification efficacy/behaviour of several models using Wekinator [25–27] by adopting similar data acquisition/processing methods, albeit with a different focus. In this work, we aim to solve the above motivations by developing a method which will allow us to observe if an AI guitar tutor can be created. To do this, we capture multimodal data (biometrics and audiovisual information) whilst a guitarist performers eight musical exercises (scales) which differ in performance conditions, and then process and visualise the returned data. We find that there are clear observable differences, within our captured multimodal dataset, when musical exercises are played on the acoustic guitar in two ways: legato (smoothly) and staccato (detached).

The paper is organised as follows: the next section will outline relevant literature in this area, including details that will inform the method used in this work, and motivate the research. Section 3 will then present the method used in this work to acquire, process and plot biometric (from the Myo armbands) and audiovisual data (camera and microphone). We then present and discuss our preliminary findings based on this method in Section 4. Finally, Section 5 will present conclusions and routes for future work.

2 LITERATURE REVIEW

This section presents subsections covering literature on musical performance assessment within the UK (Section 2.1), the classification of musical behaviours (Section 2.2), musical performance and HCI (Section 2.3), and ML within education (Section 2.4).

2.1 Musical Performance Assessment within the UK

Within the UK, assessment boards such as the Associated Board of the Royal Schools of Music (ABRSM), Rockschool, and Trinity College London assess the performance quality level of music students via graded exams. In these exams, an examiner will sit and listen to the student perform songs and technical exercises, which vary in difficulty and technical prowess, ranging from grade level one (beginner) to eight (expert). These three mentioned UK music exam boards have similarities in their technical and artistic evaluation of students' performance on differing instruments. At acoustic guitar grade one, all three music exam boards require the student to perform various technical exercises (e.g., scales) and three pieces of music [1, 17, 28]; see Table 1 for their differences and similarities at grade one (within our remit). However, these technical exercises vary. The scope of the requirements per exam board also varies, as for example, Rockschool is more oriented towards popular guitar performance but ABRSM and (according to which syllabus is sat)

Table 1. A table showing the similarities and differences between the three shown music exam boards in the UK at the time of writing, for acoustic guitar, within their respective grade one (beginner) syllabi.

Board	Guitar Style	Notation Style	No. Pieces	Scales	Scales Range (Octave)	Scales Tempo	Stroke Styles	Chords
ABRSM [1]	Classical	Standard	3	G and F majors A and E minors (natural or harmonic)	1	96BPM (thumb) 48BPM (fingers)	Tirando Apoyando	None
Rockschool [28]	Acoustic	Standard + tab	3	C major A natural minor Pentatonic: E minor, A minor and G major	1	70BPM	Plectrum	Open chords: A, D, E, C and G majors A, D and E minors Power chords: B5, A5 and D5
Trinity College London [17]	Acoustic	Standard + tab	3	C and G majors. A natural minor.	1	72BPM	Plectrum Fingerstyle	Sequence in C major: I-V7-I

Trinity College London are more oriented towards classical guitar performance. This is important to note because the focus of the exam board, or syllabus sat (e.g., Trinity College London's classical or acoustic guitar syllabus) will affect the specific performance styles/practices attributed to the guitar.

2.2 Classifying Musical Gesture

Authors in the field of musical performance and HCI have investigated the use of wearable interfaces to classify musical gesture using orientation data, through ML algorithms such as deep learning [10] and more general classification models [9]; others have looked at classifying EMG data with neural networks [13]. Studies investigating optimal data processing methods when working with EMG information have shown that the mean absolute value (MAV) is the best feature extraction method [2]. The MAV is an estimate of muscle amplitude of the arms and can be represented by

$$MAV = \frac{1}{N} \sum_{k=1}^{N} |X_k| \tag{1}$$

where X_k corresponds to kth model input, and N to the input sample size. Using the MAV as a feature extraction method for EMG signals is supported by several studies within this emerging space between music performance/composition and HCI [5, 12].

The classification of audio signals for purposes such as genre classification has been explored for a long time [32]. Other studies have investigated how audio signals can be used with orientation biometrics, and without, to affect the classification process [9]. The affordances of using orientation biometrics, rather than audio signals in isolation, have been shown to give us a good level of classification efficacy, via deep learning, regarding instrumental violin technique [10]. In the same work, applying technique classification (from the perspective of violin performance) to a feedback tool has been noted to be of importance; other authors have noted the significance of utilising virtual reality (VR) with the Myos for visualising musical performance information, which could be applied to the educational domain regarding performance feedback (as our work later intends to do). In [9], performance technique is investigated on the violin instrument using orientation data (from Myo armbands) within set conditions, such as simple musical phrases and set windows of time, in order to observe, structure and understand the data.

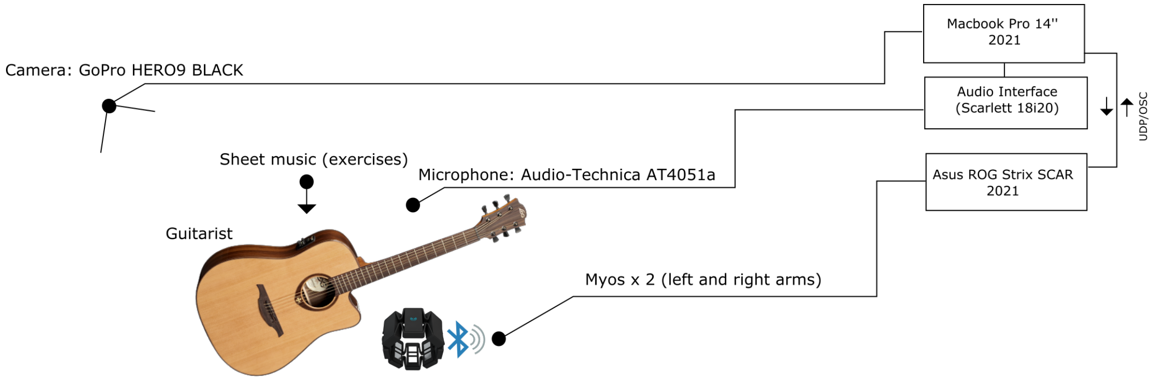

Fig. 2. Pipeline of the multimodal recording method used in this work, including hardware used (where Myo armbands can be seen) and communication lines.

Our previous work [25–27] investigated how musical gestures for the piano (and gestures not using instruments ('in the air')) can be classified using biometric data, from the Myo armbands, with varying levels of efficacy, using continuous (regression) and classifier models in Wekinator (an open access ML software based on the Waikato Environment for Knowledge Analysis (WEKA) framework); where the classification efficacy and mapping behaviour of such models was compared and discussed. The work established a developing method for processing EMG data for classification purposes during musical performance, which this work uses albeit in a different direction (towards developing an AI instructor during guitar performance).

2.3 Musical Performance/Composition and HCI

Today, composers are using game engines to explore multimodal ways of communicating musical information and develop innovative compositional methods. Extended reality (XR) composers [14, 15] are using mulitmodality to communicate musical information and explore how physical instruments can connect with virtual ones via digital interfaces. Other composers are using wearable interfaces, such as the Myo armbands, to embody and sonify (create sound from data) physiological information both within the physical [31] and digital spaces [7] (including mixed reality (MR) [8]). Other authors using Myo armbands to classify musical gesture have reported the potential improtance of using VR to visualise musical performance information [30]. Using wearable sensors to sonify bodily data allows such composers to find new methods for composing music and gesturally control sound more naturally (e.g., such as the intentions behind the much earlier Theremin). Therefore, elements of such established processes can be used within the realm of music instrument education, such as the utility of XR to achieve artistic outcomes.

2.4 Machine Learning and AI within Education

Studies within the broad field of education have used ML to predict student performance/engagement, mark student work and improve student retention [16]. Based on such work, the application of ML in education is significant because it has the ability to improve the learning experience of students. In a more focused view, ML has also been used towards education within specific professional practices such as medicine, where AI models have evaluated surgical performance skills of surgeons using VR to train [34]. Artificial intelligence (AI) has been used within other professions such as sports to provide technical feedback on technique, notably used within ping pong [18], where the movement of the

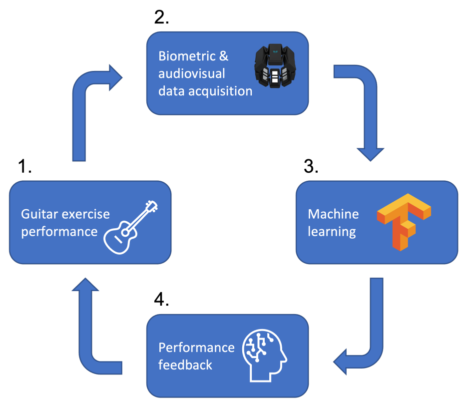

Fig. 3. Our projected overall method (pipeline) for this work. In this paper, we address points 1 and 2 on the pipeline.

ping pong racket was monitored using sensors measuring orientation data and classified using a neural network (NN) and other ML algorithms. In this work, the feedback tool operated in real-time, was especially designed for use by beginner players, was noted to be low cost and able to be used in the absence of a sports coach. There is a notable lack of studies investigating a similar approach within instrumental music performance, including how the learning experience is affected between learning from a human tutor versus an AI tutor.

3 METHOD

This section navigates the hardware used in this work (Section 3.1) and the software development/data processing steps (Section 3.2). Overall, we use the multimodal method seen in Figure 2 and we address points 1 and 2 of Figure 3, showing the overall intended steps to realise this enquiry. The first author acts as the participant to generate all data.

3.1 Hardware

To realise this work, we used the following hardware, ranging from wearable interfaces to audiovisual equipment.

3.1.1 Myo armbands. Myo armbands (see Figure 2) are wearable interfaces that communicate two types of biometric information about the wearer: orientation and muscular amplitude (EMG). EMG data are communicated at a rate of 200Hz and orientation data (from the inertial measurement unit (IMU)) is communicated at 50Hz [19], both within a range of <15m. They are communicated over Bluetooth, where the computer receiving the data uses a dongle to receive the Bluetooth information. Orientation data from the Myo IMU communicates three types of data: acceleration, gyroscopic and quaternion. To measure EMG information, the Myos have eight non-invasive electrodes that sit atop the skin. Communicated EMG data has a floating point output between -1 to 1, which is bipolar. We use two Myo armbands, worn on the left and right forearms, to capture biometric information. These armbands are worn at a fixed reference point to help eliminate skewed data through varying placement of the armbands.

3.1.2 Audio equipment. We used a microphone (Audio-Technica AT4051a) and audio interface (Scarlett 18i20) in this work to capture audio information. We used a microphone instead of a cleaner (low noise) line-in signal from an electro-acoustic guitar to qualify most acoustic guitars and environmental conditions guitarists may find at home (in preparation for the next phase of this research when we develop our AI learning tool).

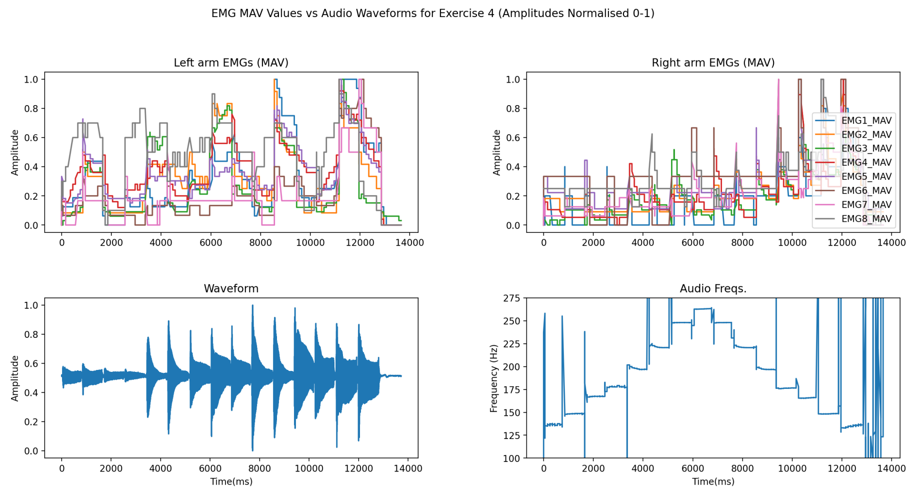

Fig. 4. A figure showing a performance of exercise 4 (legato performance of the C major scale) from the participant. Here, the crescendo (gradual increase of volume) can be seen both in the right arm EMG values, as well as the audio waveform.

3.1.3 Video equipment. We used a GoPro HERO9 BLACK camera to capture videos of exercise performances. We deemed video information useful to capture because it allows for pairing captured data with visual reference points (i.e., illuminating which technique the guitarist used at a particular point in time). As the video frames were captured, we can scrub through each captured video for identifying precise reference points in relation to the biometric and audio data. We captured video data to provide a later opportunity to use gesture recognition on such video data, if we believe it useful to do so (using a framework such as Google's MediaPipe).

3.1.4 Computers. We used a Macbook Pro 14" (2021) and an Asus ROG Strix SCAR (2021) to receive, process and acquire multimodal data. Two computers were networked and used to send received and processed biometric information via user datagram protocol (UDP) and open sound control (OSC). The Macbook was used to acquire and export all multimodal data (biometrics, audio and video) and the Asus laptop was used to receive, process and send biometrics to the Macbook. The two computers were networked in order to ease CPU stress from running both processes at once on one computer (see Figure 2). Previously, we conducted the experiment using one computer, but the musical exercises were heavily undersampled due to intense CPU stress.

3.1.5 Acoustic guitar. We use a Fender T-Bucket 300CE electro acoustic guitar for this study.

3.2 Software Development and Multimodal Data Acquisition/Processing

Software was developed in Max 8 (a visual programming environment) for acquiring and processing biometrics from the Myo armbands, as well as audiovisual information (camera and microphone data). Biometrics were acquired in Max 8 and then the MAV (as discussed in Section 2.2) was calculated for each EMG reading of the eight Myo electrodes (16 in total over both Myos worn on the left and right arms). We also used MyoMapper to capture Euler orientation data [11]. In total we captured the following data fields during acquisition for both Myos, stored in respective Myo CSV files: index number, time(ms), EMGs 1–8 without MAV calculation, EMGs 1–8 with MAV calculation, Euler orientation (Roll, Pitch, Yaw), recorded audio signal information (detected MIDI note, audio frequency (Hz), frequency confidence, audio

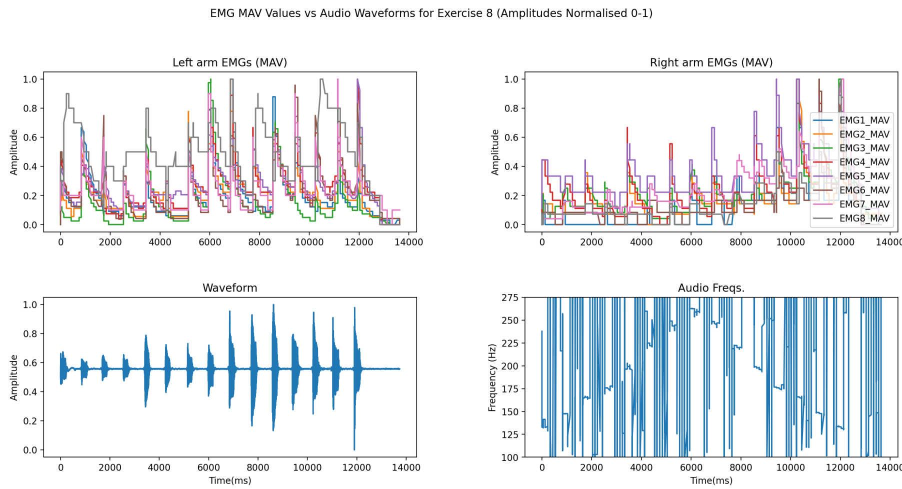

Fig. 5. A figure showing a performance of exercise 8 (staccato performance of the C major scale) from the participant. Here, the crescendo (gradual increase of volume) can be seen both in the right arm EMG values, as well as the audio waveform.

file duration (ms)), recorded video information (frame number), global time information (hours, minutes, seconds), musical information (bar number, beat number, set metronome value of exercise, and expected MIDI notes of exercise); comprised of 33 column fields for each CSV file. During acquisition of all data, a metronome was used to keep the guitarist in time whilst performing the musical exercises described in Section 3.3. A metronome speed of 70BPM was used, based on the real-world conditions found in Table 1 for scales tempo. We used a one bar count in to prepare the guitarist to begin recording for each exercise. During recording, each registered beat of this metronome was used to reset the MAV calculation for each EMG electrode (i.e., reset the sample length of the calculation) and therefore create specific observable windows of time for each note in the scale; allowing us to pair biometric behaviour (of both arms) with windowed moments of time indicative of specific musical information (where each beat of the scale is played every c. 857ms over 14s when the tempo is 70BPM).

We organised all of the captured biometric and audiovisual information within the developed software in Max 8 by recording each source at the same time (triggered by a single message from the system to begin recording) and then sending important metrics (dependent on each source, e.g., video frame number) to a shared data table for all sources (biometrics, audio and video). We also captured the MIDI note values of the scales (as they should be on the sheet music), as well as bar/beat number, within this table. This kind of information was captured so we could synchronise all data sources later. To help synchronise each data source for later analysis, each of the filenames belonging to a data source (i.e., biometrics, audio and video) followed a naming convention for organisational ease: SessionNo–ParticipantNo–ExerciseNo–IterationNo–Time(hour)–Time(minute–Time(seconds)–Date(day)–Date(month)–Date(year). A similar method was used by [10]. Using this automated filename convention also ensured that data was not overwritten.

Following acquisition and processing (labelling, scaling and feature extraction), the data in Max 8 were exported as a CSV file (including biometrics and audio visual metrics/metadata), and then processed in Python. We wrote a script in Python to automatically import the captured CSV files of biometrics, structure them (according to participant number and exercise number), process them (normalise ranges) and then plot them for an exploratory analysis of the data through visualisation. In the same script, we also imported audio (.wav) and video files (.mov). Audio files were used for comparing the biometric activity with the captured musical activity.

Fig. 6. A view of mixed reality work *Membrana Neopermeable* as seen from within an Oculus Quest 2, created by the first author, showing the user playing a virtual guitar through gesturally interacting with it.

3.3 Guitar Exercises

The first author developed eight exercises on the guitar instrument based on the real-world conditions of UK exam boards outlined in Table 1. All our exercises use the C major scale over a range of an octave, performed using a plectrum, as used by two of the three exam boards (Rockschool and Trinity College London). Similarly, these scales were notated using standard notation and tablature (tab). All exercises use precise fingering patterns to isolate biometric data to individual fingers (see Appendix A). We designed these scales in different conditions with regards to dynamics (amplitude) and technique (legato–smoothly–and staccato–detached) in order to spot unique biometric patterns pertaining to each technique. Exercises 1 to 4 are played legato and exercises 5 to 8 are played staccato. Exercise 1 is played piano (quietly), 2 is played mezzo forte (moderately loud), 3 is played forte (loud) and 4 is played with a crescendo, ranging from piano to forte. These changes in dynamics are precisely the same for exercises 5 to 8, albeit played staccato. An example of such exercises can be seen in Appendix A.

4 DISCUSSION

In this section, we presented the preliminary findings of this ongoing work (Section 4.1) and planned responses to such findings (Section 4.2).

4.1 Preliminary Findings

We conducted an experiment using one participant (first author of this paper), using musical exercises of the C major scale played in eight different variations (see Appendix A for an example of these). We found that there seems to be an individual relationship between the acquired multimodal information and different performance techniques (i.e., piano, mezzo forte, forte and crescendo dynamics). Figure 4 shows the participant (guitarist) performing a C major scale (exercise 4–see Appendix A), played legato, using a crescendo over time (from piano to forte) to affect the loudness of the scale. This exercise was devised to see if there is a difference or similarity between playing a scale legato (smoothly) or staccato (detached), and if amplitude affected a pattern within arm muscles contraction. Upon observation, Figure 4 shows that the contraction amplitude of the right arm (top right plot) indeed gradually gets more dynamic in line with the crescendo dynamics of the scale (see bottom left of the plot showing the captured audio waveform over time).

Figure 5 shows the guitarist performing a C major scale using the same scalic conditions as in Figure 4, however played staccato (detached–compare the waveform of Figure 4 with the waveform of this figure). Comparing Figure 5 with Figure 4, we can see that the right arm muscle contraction amplitude gradually increases in line with the same pattern found in Figure 4 (top right plot). This is promising, as it shows that a similar right hand performance behaviour occurs between both different conditions of the scale (legato vs staccato).

When comparing Figures 4 and 5, we also see that the left hand EMG values (responsible for fingering notes on the fretboard) are distinctive (compare top left plot on both figures). Specifically, the left hand plot for Figure 4 shows that EMG signals for notes in the scale are smoother in shape, compared to the left hand plot for Figure 5 where the signals are sharper and more pointy. This is also promising because the contour and shaping of both sets of signals follow the waveform and the behaviour we would expect when we play notes on the guitar in such a manner (legato vs staccato).

4.2 Responses to Current Findings

Based on the findings outlined in Section 4.1, we are happy that some patterns exist when playing a musical exercise in different conditions. However, we understand that this is relative to a sample of one participant. Therefore, we wish to record more participants and see if this pattern is generalisable. If a generalisable pattern is discerned amongst a larger sample of guitar players, we intend to apply deep learning models, e.g., as discussed in [10] (i.e., LSTM and CNN). This will allow us to pair our observations within biometrics and musical intent when playing the acoustic guitar. In turn, allowing us to develop a model which can predict when guitar techniques occur, when they should occur and what kind of feedback can be given.

We believe that applying our current findings to the development of an AI led virtual music instructor could result in numerous benefits, particularly with regards to democraticising access to musical instrument (guitar) education. However, we do also consider that the limitations of our approach are that using this feedback system could lead to specific styles of playing the guitar, potentially limiting instrumental creativity, if used widely; where this 'richness' of playing in the real-world is typically captured and communicated at the human level, by our current understanding. We intend to explore the latter further and import human feedback (via expert guitar performers) to enhance this process. We also intend to survey student and amateur guitar players and receive their feedback on our intended system, contributing to its development.

5 CONCLUSIONS AND FUTURE WORK

In conclusion, this developing work has shown that there are some clear patterns in the captured multimodal datasets when playing musical exercises on the acoustic guitar, giving us the potential to differentiate instrumental performance technique, using our method. This is promising and means that this ongoing work shows evidence and promise for answering our current research enquieries, such as how can musical techniques be classified. It also allows us the foundation to begin questioning how a virtual guitar instructor can be developed using AI. In our future work, we intend to apply pattern analysis on the EMG time series datasets to fully explore how we may begin to use deep learning to build a classifier/autonomous AI (see Figure 3); we will also be evaluating this process via participant feedback (expert guitar performers) and using model accuracy metrics. We will also be using what we have found so far to explore the more creative outcomes of the overall enquiry, such as how musical riffs and licks for the guitar (i.e., non-scalic exercises) can be acquired, analysed and learnt. We also intend to build upon previous research in this area from the first author (see Figure 6) with this research enquiry, exploring how 3D virtual elements can be used within game engines (VR/MR) to provide intuitive feedback to guitar students. We will also be building upon our research in [27] to explore how the method presented in this work can be used with the game engine mechanics we built in that enquiry to create interactive music and visuals from EMG data (which is not native to current commercial VR equipment, despite being musically beneficial regarding HCI). This will allow us to decide which type of medium the instructor should be used within and the creative affordances of such medium.

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REFERENCES

[1] ABRSM. 2019. Guitar Grade 1. https://tinyurl.com/3euz48xt [Online; published 2019].
[2] Zainal Arief, Indra Adji Sulistijono, and Roby Awal Ardiansyah. 2015. Comparison of Five Time Series EMG Features Extractions Using Myo Armband. In *2015 International Electronics Symposium*. 11–14.
[3] Robert S. Armiger and R. Jacob Vogelstein. 2008. Air-Guitar Hero: A real-time video game interface for training and evaluation of dexterous upper-extremity neuroprosthetic control algorithms. In *2008 IEEE Biomedical Circuits and Systems Conference*. 121–124.
[4] Gobinath Aroganam, Nadarajah Manivannan, and David Harrison. 2019. Review on Wearable Technology Sensors Used in Consumer Sport Applications. *Sensors* 19, 9 (2019). https://www.mdpi.com/1424-8220/19/9/1983
[5] Jamie Bullock and Balandino Di Donato. 2016. Approaches to Visualising the Spatial Position of 'Sound-objects'. (July 2016). https://tinyurl.com/2ha2xhv7 Publisher: BCS Learning & Development.
[6] Eleanor Busby. 2018. Poorer children in UK are being priced out of learning to play musical instruments, report warns. https://tinyurl.com/mpvpm7uz
[7] ChrisRhodesMusic. 2022. Chris Rhodes - Deep Blue AIr (2020). https://tinyurl.com/5n7wky6x
[8] ChrisRhodesMusic. 2022. Chris Rhodes - Membrana Neopermeable (2022). https://tinyurl.com/y97vh2sz
[9] David Dalmazzo and Rafael Ramírez. 2019. Bowing Gestures Classification in Violin Performance: A Machine Learning Approach. *Frontiers in Psychology* 10 (2019), 344. https://www.frontiersin.org/article/10.3389/fpsyg.2019.00344
[10] David Dalmazzo, George Waddell, and Rafael Ramírez. 2021. Applying Deep Learning Techniques to Estimate Patterns of Musical Gesture. *Frontiers in Psychology* 11 (2021).
[11] Balandino Di Donato, Jamie Bullock, and Atau Tanaka. 2018. Myo Mapper: a Myo armband to OSC mapper. Virginia Tech, Blacksburg, Virginia, USA, 138–143. http://www.nime.org/archives/
[12] Balandino Di Donato, James Dooley, Jason Hockman, and Simon Hall. 2017. MyoSpat: A hand-gesture controlled system for sound and light projections manipulation. Shanghai, China. http://www.open-access.bcu.ac.uk/5002/ Meeting Name: ICMC 2017.
[13] Çağrı Erdem, Charles Martin, Qichao Lan, Jim Tørresen, Julian Fuhrer, and Alexander Jensenius Refsum. 2020. Towards Playing in the 'Air': Modeling Motion–Sound Energy Relationships in Electric Guitar Performance Using Deep Neural Networks. 8.
[14] Rob Hamilton. 2015. Carillon. https://tinyurl.com/4j5e9hwp
[15] Keep.It.Human. 2020. Duel of Strings (5k - 360 video): Karin Kellqvist vs. Ricardo Climent- Full concert (ambisonics). https://tinyurl.com/4beakder
[16] Danijel Kucak, Vedran Juricic, and Goran Dambic. 2018. Machine Learning in Education - a Survey of Current Research Trends. In *DAAAM Proceedings* (1 ed.), Branko Katalinic (Ed.). Vol. 1. DAAAM International Vienna, 0406–0410. https://tinyurl.com/3ywc9abn
[17] Trinity College London. 2019. Acoustic Guitar. https://tinyurl.com/2p9645u2 [Online; published 2022].
[18] Kevin Ma. 2020. Artificial Intelligence Aided Training in Ping Pong Sport Education. In *2020 Second International Conference on Transdisciplinary AI (TransAI)*. 43–49.
[19] Kristian Nymoen, Mari Romarheim Haugen, and Alexander Refsum Jensenius. 2015. MuMYO — Evaluating and Exploring the MYO Armband for Musical Interaction. In *Proceedings of the International Conference on New Interfaces for Musical Expression*.
[20] Royal Philharmonic Orchestra. 2018. *A New Era for Orchestral Music*. Technical Report. UK.
[21] Sungmee Park and S. Jayaraman. 2003. Enhancing the quality of life through wearable technology. *IEEE Engineering in Medicine and Biology Magazine* 22, 3 (2003), 41–48.
[22] Dipesh S. Patle, Davide Manca, Salman Nazir, and Swapnil Sharma. 2019. Operator training simulators in virtual reality environment for process operators: a review. *Virtual Reality* 23, 3 (Sept. 2019), 293–311.
[23] Jack Purcher. 2021. Apple wins a Major Apple Watch Patent that supports Face ID and Sports Performance Analysis via in-band Sensors. https://tinyurl.com/2p83puce
[24] Jack Purcher. 2021. The U.S. Patent Office has Published Facebook's Patent behind their Future AR Glasses Wristband Input Device. https://tinyurl.com/c9zhhcy9

[25] Chris Rhodes, Richard Allmendinger, and Ricardo Climent. 2019. New Interfaces for Classifying Performance Gestures in Music. In *Intelligent Data Engineering and Automated Learning – IDEAL 2019 (Lecture Notes in Computer Science)*, Hujun Yin, David Camacho, Peter Tino, Antonio J. Tallón-Ballesteros, Ronaldo Menezes, and Richard Allmendinger (Eds.). Springer International Publishing, Cham, 31–42.

[26] Chris Rhodes, Richard Allmendinger, and Ricardo Climent. 2020. New Interfaces and Approaches to Machine Learning When Classifying Gestures within Music. *Entropy* 22, 12 (2020), 1384. https://www.mdpi.com/1099-4300/22/12/1384 Number: 12.

[27] Chris Rhodes, Richard Allmendinger, and Ricardo Climent. 2022. Classifying Biometric Data for Musical Interaction Within Virtual Reality. In *Artificial Intelligence in Music, Sound, Art and Design (Lecture Notes in Computer Science)*, Tiago Martins, Nereida Rodríguez-Fernández, and Sérgio M. Rebelo (Eds.). Springer International Publishing, Cham, 385–400.

[28] Rockschool. 2019. Acoustic Guitar. https://www.rslawards.com/rockschool/graded-exams/acoustic-guitar/grade-1/ [Online; published 2019].

[29] Ruben C. Rodriguez. 2019. *Rocksmith All Nite: Technology-Mediated Guitar Learning in an Online Affinity Space.* Ph.D. The University of Texas at San Antonio, United States – Texas.

[30] John Edel Tamani, Jan Christian Blaise Cruz, Joshua Raphaelle Cruzada, Jolene Valenzuela, Kevin Gray Chan, and Jordan Aiko Deja. 2018. Building Guitar Strum Models for an Interactive Air Guitar Prototype. In *Proceedings of the 4th International Conference on Human-Computer Interaction and User Experience in Indonesia, CHIuXiD '18 (CHIuXiD '18)*. Association for Computing Machinery, New York, NY, USA, 18–22.

[31] Atau Tanaka. 2019. Sarah Nicolls performs Suspensions, by Atau Tanaka. https://tinyurl.com/y9ezkr8d

[32] George Tzanetakis and Perry Cook. 2002. Musical genre classification of audio signals. *IEEE Transactions on Speech and Audio Processing* 10, 5 (2002), 293–302.

[33] Maarten Walraven-Freeling. 2021. The pandemic has changed music education for good. These are the opportunities. https://tinyurl.com/9xmpcxx6

[34] Alexander Winkler-Schwartz, Vincent Bissonnette, Nykan Mirchi, Nirros Ponnudurai, Recai Yilmaz, Nicole Ledwos, Samaneh Siyar, Hamed Azarnoush, Bekir Karlik, and Rolando F. Del Maestro. 2019. Artificial Intelligence in Medical Education: Best Practices Using Machine Learning to Assess Surgical Expertise in Virtual Reality Simulation. *Journal of Surgical Education* 76, 6 (Nov. 2019), 1681–1690. https://tinyurl.com/renpv99t

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