Towards The Future Practice Room: Empowering Musical Pedagogy through Hyperinstruments

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ABSTRACT
Music education is a rich subject with many approaches and methodologies that have developed over hundreds of years. More than ever, technology plays important roles at many levels of a musician's practice. This paper begins to explore some of the ways in which technology developed out of the NIME community (specifically hyperinstruments), can inform a musician's daily practice, through short and long term metrics tracking and data visualization.

Keywords
Hyperinstruments, Pedagogy, Metrics, Ezither, Practice Room

1. INTRODUCTION
Pursuing a higher education degree in music today, one will observe first-hand the increasing prominence of technology in the life of practicing musicians. It is not uncommon to see musicians recording ensemble practices and private lessons with portable hand-held recorders or laptops. The field recorder is often thought of as one of the most important inventions for ethno-musicological purposes but its impact on western music *practice* is also very significant. Portable recording devices however are just one of the simplest ways in which technology permeates today's learning environments.

Many music programs (at the university and even primary/secondary levels) now have "keyboard labs" where a group of students gather around computers with headphones and MIDI keyboards, engaging with interactive musicianship skills software. Computer-assisted learning has gained popularity in recent years and most interactive software application cover topics as diverse as aural identification/ear training, rhythm skills, scales, harmony, and other theory topics. Auralia [3], Practica Musica [1], EarMaster [6], Ear Conditioner, are a few of the many applications being used in music schools around the world everyday, which enable musicians to be conducted through aural and theory exercises with a virtual guide. They operate around the basic principle of receiving symbolic (MIDI) input from users playing a digital piano keyboard or via mouse/keyboard computer input. While the effectiveness of these types of software has resulted in their adoption in the curriculum of many schools, there are many restrictions as a result of the limited (instrumental) scope of the input modalities.

Firstly, computer-assisted music training currently gauges a (non-pianist) musician's abilities via input other than their actual instrument. While basic keyboard skills are important for all musicians to acquire (at least in the Western tradition), it is important to engage and assess the student on their actual instrument or voice.

This leads to the second restriction, namely that the software is listening to the musician's input in a limited manner. Input via a MIDI keyboard is a step in the right direction; however, it does not provide insight into the acoustical and physical dimensionalities, two elements that are crucial to musical performance. This is what brings music students in front of instructors, tutors, and gurus, every day—years of experience, knowledge, and human musicianship.

There are many more ways in which technology is influencing the environment in which musicians now learn. Universities such as McGill University in Montreal (and many others) have been pushing the idea of "distance learning" in many of their disciplines [4, 5, 9, 11]. In music education this enables educators (whether on tour, or music teachers living in other countries) to administer lessons from afar over video conferencing technology. The idea of anthropomorphic robotic music instructors that are capable of responding to human performers [16] has even been proposed. Recently, Percival presented an interesting approach to computer-assisted violin practice and a good overview of the current state of "Computer-Assisted Musical Instrument Tutoring" (CAMIT) musical in [15]. In line with the goals of this research, Percival places a strong emphasis on creating systems that concentrate a musician's interactive practice exercises on areas that need the most practice, rather than the (relatively naive) general theory based software approaches that currently exist.

While it seems traditional musicianship training (sight-reading, ear training, rudiment training, chord identification, etc.) in the form of classroom activities, private exercise in the practice room, and from real-life engagement with other musicians and performances will always be essential to the future musical learning environment, the musical classroom is an ever-expanding environment, moving beyond its traditional latitude. Today, searching "guitar lesson" on YouTube yields nearly 1 million results, tomorrow who knows?

This research asks how can we advance technology to supplement ones musical practice, both inside and outside of scheduled class times and lessons? Can developments in NIMEs and hyperinstruments provide musicians and educators alike, focused insight into the acoustical and physical dimensionalities of a musicians practice? This research begins to parameterize and visualize this information in an attempt to inform musicians and educators, following musical pedagogy into new domains. To that end, this paper explores cross-modal metrics, tracking the day-to-day, and long-term evolutions of a musician's practice. Specifically, this paper focuses on a subset

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of analyzed performance metrics pertaining to the player's physical performance of various bow strokes (articulations), which is uniquely afforded through the use of a sensor-modified instrument called the Ezither. In addition to metrics and statistical measures, various visualizations and statistical representations are proposed, which can provide musicians and instructors with nuanced information about the performers playing at a glance.

2. SYSTEM DESIGN AND IMPLEMENTIONATION

2.1 The Ezither

The Ezither [10] is a custom 10-string zither-like hyperinstrument that resembles other members of the citre family. Embedded within the instrument are a number of sensors capturing performance data. These include a force-sensing resistor placed either underneath or on the side of each bridge (depending on the intended use), five buttons, and three potentiometers. Additionally, the Ezither is played with a modified bow that connects directly to the instrument and reports gestural data from a triple-axis accelerometer. All data is sent together from the main instrument body over USB MIDI.

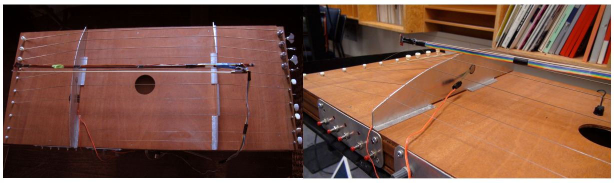

Figure 1 – The Ezither Hyperinstrument and Bow

2.2 Data Collection

This section provides an overview of the data collection process used in this research. A brief overview of the software used to collect the data is discussed in 2.2.1, followed by an overview of the performance data collected in 2.2.2.

2.2.1 Nuance

Because a primary concern of this work was for the musician to independently record his daily practice over an extended period, it was important that the data capturing system required little to no programming or "patching" to operate, and that it could be easily learned and used. As such, the Ezither practice sessions where recorded using Nuance [8], a general purpose multi-track recording solution for multimodal data sources. Geared towards machine learning and musical data mining, Nuance enables nearly any musical sensor system and instrument communicating over serial, MIDI, and OSC to synchronously capture its data to disk in .wav audio format.

Much like typical digital audio workstations (DAWs), Nuance provided the musician a drag-and-drop interface in which individual tracks could be created for each data stream coming from his instrument (audio for a microphone recording, and MIDI recorders to capture each sensor in use). Additionally, the project/session layout (Figure 2) could be saved and opened during each practice session.

Nuance was used to record a variety of data sets for the Ezither performer. The ultimate goal was to capture the variability of the player's performances under scenarios ranging from typical practice routines to improvisation. The following section describes in greater detail the data sets collected spanning these grounds.

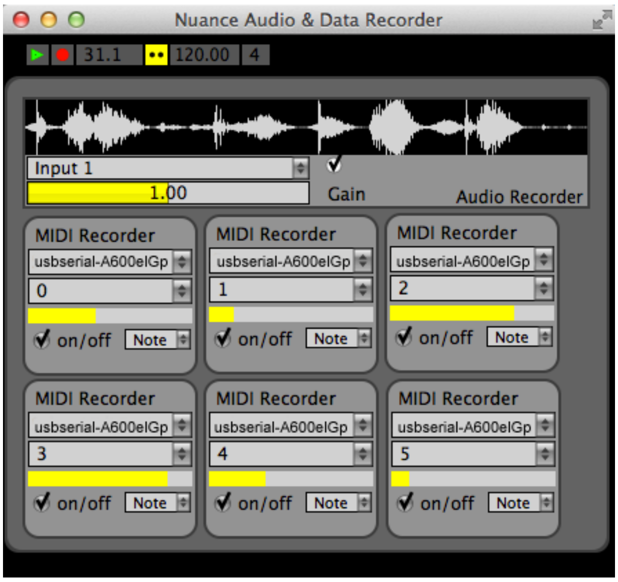

Figure 2 – Screenshot of Nuance Recorder

2.2.2 Ezither Data

For roughly seven months between August 12th 2011 and March 22nd 2012, the Ezither performer regularly recorded his practice. As this was a new, custom-built instrument, the performer was at a beginner level, and had no prior experience playing a bowed stringed instrument (although he was a trained musician and composer on other instruments). The total data collected consisted of sixteen practice sessions over the seven-month period.

During each session the performer recorded four discrete data sets. The first data set (D1) targeted the practice of various bow strokes including *Detaché, Martelé, and Spicatto.* During a session each stroke was played for roughly 30 seconds in up-bow down-bow succession at 120 beats-per-minute. The player was restricted to playing on one string (the lowest string, C) of the instrument to limit the effect of string and position changes on stroke performance.

The second data set (D2) aimed to capture the performer's variability in tempo performance. As such the performer arpeggiated up and down the open-strings of the instruments at three tempi, *Andante* (80bpm), *Moderato* (110bpm), and *Allegro* (140bpm). The passage was recorded in up-bow down-bow succession for roughly two-minutes.

In data set 3 (D3) the performer repeated a melody for about two minutes. The melody was played at a fixed tempo (100bpm) however the line was less-constrained than data sets D1 and D2 in that it was not confined to a single string or moving up and down the strings linearly. The melody was a simple 4-measure long line as noted in Figure 3. As the performer was a beginner on the Ezither, the melody line mostly moved in a scalar fashion, with one small intervallic leap in the last measure.

Figure 3 – Melody repeated in dataset 3 (D3)

Lastly the final data set (D4) was purely improvisational. No instructions were given to the performer other than he should play whatever he liked. The performer was free to bow the notes, pluck the notes, and work his way through 2-minute long mini improvisations (while listening to a metronome at 120 bpm).

As this research focuses on metrics pertaining to the physical dimension of bowed string performance, specifically, the player's performance of various bow strokes over time which are unique captured by sensors (as opposed to audio-based metrics like tempo which are now also being explored), the remainder of this paper will look at data set D1.

2.2.3 Definition of Bow Articulations

The three bow strokes played in D1 included detaché, martelé, and spiccato. While definitions may vary slightly, detaché is a stroke in which only one bow is performed per note, with equal weight (pressure) in between strokes. Detaché appears to mean detached, however, it does not mean detached in the typical sense (that the bow leaves the string), and some refer to it being detached in that there are no slurs between notes.

Martelé is a hammered stroke with a strong crisp bite at the beginning of the stroke, which is immediately relaxed through the remainder of the stroke.

Spiaccto is a bounced stroke where the bow leaves the string. It is lighter than detaché and martelé and is often played at the balance point (center) of the bow.

3. PERFORMANCE ANALYSIS

3.1 Bow Articulation Technique Metrics and Statistics

This section focuses on various aspects of how the performer played various bow-strokes. Building off acoustic studies in [2], recent work in the field concerning bowing technique has focused largely on utilizing low and mid-level features to automatically classify bow strokes or articulations [7, 14, 18, 19]. This research instead looks at high-level features extracted from different bow articulations and how they relate to the overall performance technique and the abilities of the performer.

3.1.1 Bow Articulation: Onset Difference Time (ODT)

The Onset Difference Time (ODT) is a feature we propose that compares the note onset times between sensors on the performer/instrument with the note onset time from the resulting acoustic output. The ODT is a useful metric in bow stroke analysis as it captures a characteristic of the performer's playing of a particular bow articulation, making it useful in both pedagogical situations as well as other contexts (e.g. bow stroke identification). This section looks at the former, detailing the ODT for different bow strokes performed by the Ezither performer and how the ODT may inform a player's practice.

Generally speaking, the accelerometer placed on the frog of the bow will detect a sudden jerk at the beginning of a stroke from stand still, or when the performer twists their wrist at the start of the succeeding note. The acoustic sound produced is determined by a number of factors, ranging from the weight placed on the strings, the location of the bow on the strings, and sometimes the speed (although a skilled performer can play fast or slow while maintaining dynamic control). Before the sound is produced, the performer gestures the start of the bow stroke, and this section compares the onset of the gesture to the acoustic output as a characteristic feature of the performer's bow-stroke performance.

By subtracting the sensor onset time from the audio onset time it is possible to determine which onset preceded the other. A negative (-) ODT would mean that the sensor onset arrived earlier than the acoustic onset (rush), whereas a positive ODT means that the sensor onset was detected later than the acoustic onset (lag). The lag and rush times for detaché, martelé, and spiccato for recording #9, data set D1, are visualized in Figure 4 alongside the mean and standard deviation of the ODTs.

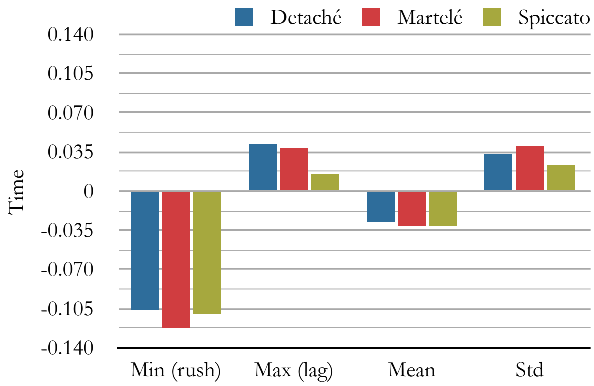

Figure 4 - Onset difference time (ODT) statistics for recording #9 dataset D1

Overall the average ODT for each bow stroke was below zero (rush), meaning the sensor (accelerometer) onset was detected earlier than the acoustic onset. This seems likely when taking the twist of the performer's wrist between notes into consideration, and the fact that the performer sets the stroke in motion, and then pressure and other dynamic/timbre control are applied. Earliest rush was detected for the performer's martelé stroke, perhaps due to the fact that the performer must apply more pressure to the strings with the bow, affecting the gesture's velocity curve.

When the accelerometer onset lags the acoustic onset, the performer continued the head of the note past the note's start. Similar lag was detected for detaché and martelé strokes and both were greater than spiccato. Of the three strokes, detaché and martelé are the most similar, with martelé requiring the easing up of pressure after the head of the note. This may account for the slightly lower maximum lag time vs. detaché, and the slightly earlier (earliest) rush time resulting from the sudden direction and pressure change between strokes.

Overall spiccato performance was the most regular in ODT when compared to the other two strokes. Detaché was slightly more regular than martelé and the performer could use these results to focus his practice to minimize the ODT or standard deviation through practice. In the future it would be useful to extend this to other bowed string instruments such as the violin, and to compare the ODT analysis from a beginner player with that of expert performers. It would be useful to further understand how the ODT contributes to the expressive qualities and acoustic output of skilled performers, and as a useful feature in other tasks such as bow stroke recognition.

3.1.2 Bow Articulation: Articulation Attack Slope

In addition to the onset difference time, another useful bow gesture metric is the (attack) slope of the bow articulation acceleration curve. Previous work by [17] parameterized min/max velocity and acceleration for bow stroke classification using accelerometers, and demonstrated a strong bond between gesture bow articulations and velocity/acceleration. The work in this section parameterizes the slope of the curve leading up to the accelerometer note onsets, which we call the Articulation Attack Slope (AAS).

Following the audio attack slope detection strategy in [12], the AAS is computed as a ratio between the magnitude difference between the start (local minima) and ending (local maxima/onset) of the attack phase, and the corresponding time difference. Figure 5 displays the entire attack phases of the detected AASs for a single detaché recording as the red lines in between onsets and their preceding local minima (valleys). The top of the figure shows the attack phase for AASs detected for the entire recording, and the bottom of the figure displays a six-note excerpt between 10.0 seconds and 12.8 seconds.

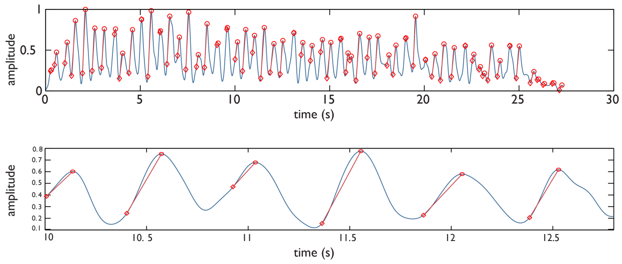

Figure 5 - Note attack slope for Ezither recording #9 data set D1, Detaché entire recording (top), 2.8-second window from 10sec – 12.8sec (bottom)

The actual AAS value as previously described is the ratio between the valley-onset magnitude difference, and the corresponding time difference. Figure 6 provides the average and standard deviations of the AAS values for each bow articulation.

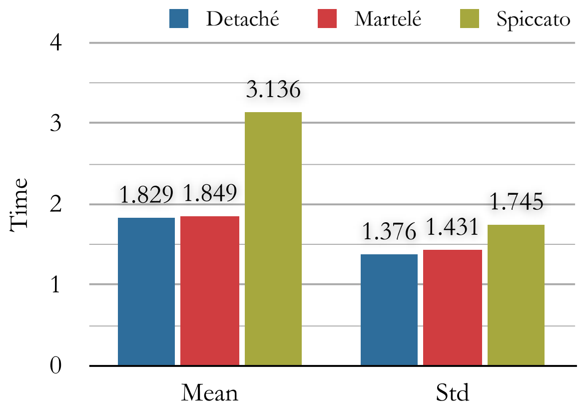

Figure 6 - Mean and standard deviation of bow stroke attack slopes for Ezither recording #9 dataset D1 detaché, martelé, and spiccato

3.2 Long-term Metrics Analysis

In the previous sections various bow performance measures were explored; the ultimate goal was to capture performance metrics (and their differences when compared to the ideal target performance) that could be used to help focus the performer's practice. Bow articulation metrics were explored, including the performer's bow-stroke and acoustic onset difference time, as well as the articulation attack slope. All of the metrics and derived statistics were visualized in various ways to inform the performer about their playing over the individual performances and recordings. In this section, the development of the performer's playing is observed by examining similar metrics and statistical measures over the course of seven months.

3.2.1 Long-Term Bow Articulation Metrics: Onset Difference Time

The Onset Difference Time was explored previously in 3.1.1 as a characteristic metric of each bow articulation. Observing statistics of a particular bow-stroke's ODT, the research showed the average ODT and its variability for a given articulation and performance. The ODT also showed how much the performer may have lagged or rushed the beat for the particular articulation and practice session recording. Thus it is useful to evaluate the ODT for each bow articulation over time, in order to evaluate the usefulness of the measure and how it can continue to inform the performer's development and practice.

Figure 7 shows the session-to-session difference between the average ODT for each practice session, for all (three) bow articulations performed. A smaller delta between sessions means that the ODT remained consistent between sessions. As illustrated in the figure, the difference between average ODTs from session to session was very close for both martelé and spiccato strokes. This can infer that (from the start) the particular onset properties of the performer's physical and acoustic actions remained regular. This is also true for the performer's detaché stroke the majority of the time, except between practice sessions five and eight. If the performer was aware of this at the time of practice, for example during practice session #6, he may have placed more focus or emphasis on his detaché stroke, to target the consistency of his detaché playing.

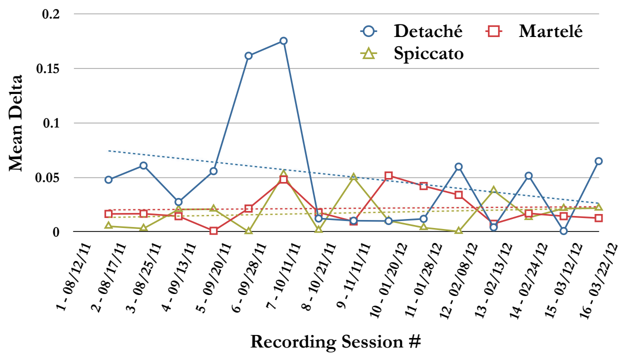

Figure 7 - Session-to-session change in Ezither articulation Onset Difference Time

3.2.2 Long-Term Bow Articulation Metrics: Articulation Attack Slope

In this section we revisit the Articulation Attack Slope, a metric that in this scenario measures the acceleration slope of the bow articulation gesture. As the nature of the physical gestures attack slope may change slightly between performer and/or playing style, this research does not compare the performer's AAS against a target attack slope for the particular bow articulation; rather it investigates the consistency of the performer's gesture over time.

Theoretically, as the performer's technique improves, the average AAS for each articulation recording should homogenize. One would hope that the performer's technique should become more consistent, leading to a regular AAS when performing a particular bow articulation. To investigate this relationship the delta in average AAS between successive practice sessions is examined and displayed in Figure 8. As expected, in the earlier practice sessions the difference in the average AAS is generally greater than in later practice sessions. The dashed trend lines show that for each of the three articulations practiced, the performer's technique improved in terms of consistency of the gesture's AAS.

The performer's best stroke (in terms of AAS regularity) was martelé, followed by detaché, and then spiccato. Greatest improvement over the sixteen practice sessions was achieved for spiccato, as illustrated by the steepest slope of the three trend lines. Martelé was the best stroke (in terms of AAS regularity) and also improved slightly greater than detaché (as illustrated by its steeper trend line). Spiccato was the weakest articulation, although the stroke showed the most improvement over time, martelé was the strongest performer overall, and detaché was a strong stroke for the performer but showed the least amount of improvement over time.

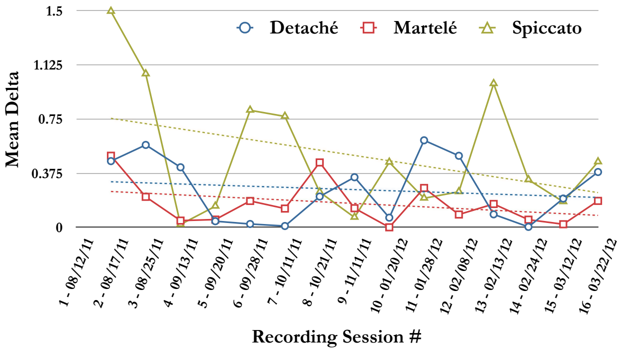

Figure 8 - Ezither average articulation attack slope difference over time for (AAS difference – solid, trend lines dashed)

Inevitably there will be variation in the AAS every time a performer plays a particular bow articulation. To further measure the consistency/regularity, and the accuracy of the performer's (physical) technique, one can also look at the change in standard deviation and range of the AAS between practice sessions. They are useful statistics in that they describe the spread of the AAS values, and how much the performer deviated from the mean AAS. Just as the change in average AAS regularizes over time if the performer's technique improves (Figure 8), the range and standard deviation of an articulation's AAS may also become more regular over time (hopefully decreasing).

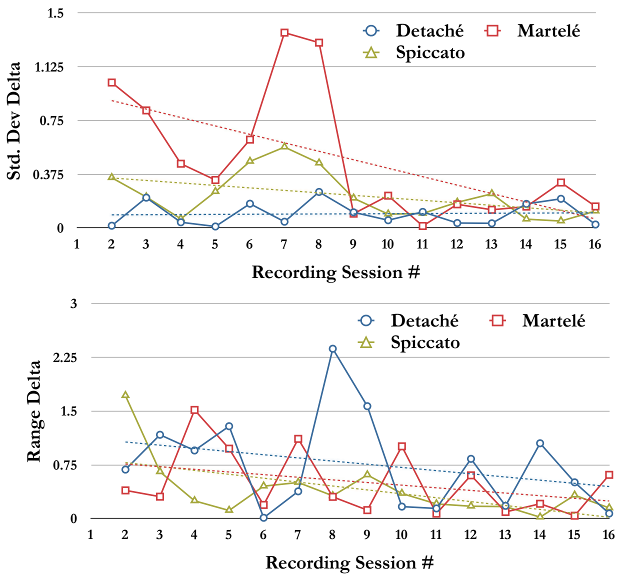

Figure 9 - Ezither articulation attack slope standard deviation (top) and range (bottom), session-to-session difference over time for (AAS difference – solid, trend lines dashed)

As illustrated in Figure 9 this is the particularly true for the Ezither performer. In terms of standard deviation of AAS, the performer's AAS standard deviation for both martelé and spiccato regularize over time. When performing detaché, the performer's AAS standard deviation remains fairly consistent, which also resembles earlier results in change in average AAS for detaché. Martelé and spiccato however become more regular over time in terms of AAS standard deviation, and all three articulations regularize in AAS range between sessions. These measurements are useful signifiers to the musician and the instructor about the overall progress and uniformity of the physical motion of the performers bow stroke articulations.

4. Conclusion

There is no doubt that the role of technology in the practice room will continue to permeate the ways in which musicians and musical educators learn and teach; interactive systems and computer assisted musical development have already been integrated into the everyday curriculum of music schools the world over. While current systems work satisfactorily for certain aspects of musical training, no readily available or widely-used system currently specializes to the individual needs of the performer, or the musical semantics of their particular instrument.

Musical performance is highly individualized in nature, and traditionally a musician learns to play in a formalized contract between the teacher (mentor, guru, master musician, etc.) and the student. Commonly the amount of time a musician spends practicing alone compared to the amount of time they spend practicing within the guidance and presence of their instructor is often less than ideal. Thus computer assisted practice offers great potential in helping musicians practice with greater understanding and focus, especially when practicing independently.

In order to enable effective and nuanced channels of understanding between musicians and the computer, this research argues that analysis not only within acoustical domain, but also from the physical dimensionalities is necessary. As such, the role of NIMEs and sensor-modified instruments (i.e. hyperinstruments) will be elemental in the future of musical pedagogy and practice. In particular, this paper focuses on string performance, and some of the possibilities when combining analysis gesture data from an accelerometer on the bow of the instrument. Exploiting the affordances of musical instruments equipped with other sensing modalities, this research attempts to highlight useful characteristics from the performers practice, including information concerning the performers ability to play various bow articulations. The metrics and statistics were evaluated at various time-scales, obtaining useful performance metrics not only in individual practice sessions, but also over a seven-month period in which the performer learned to play his instrument (the Ezither) having never played the instrument before.

In analyzing the Ezither performer's practice, a concise set of statistical measurements and visualizations are presented. There are many other features, statistical measures, and visualization techniques that can be observed and provide useful information about performance. However, this research chose to focus on the following selection of common statistical tools for a number of reasons: (1) Statistics, (1a) Average, (1b) Standard Deviation, (1c) Range, (2) Visualizations, (2a) Bar graph, (2b) Line plot.

Firstly, the experiments and analysis tools proposed should not require mathematicians and scientists to be used or understood. As the ultimate goal is to eventually support these metrics in the regular practice room or bedroom of practicing musicians, there was a strong desire to keep the metrics and visualizations as simple and straightforward as possible. Relational observations are also desired, so many of the visualizations presented were chosen as they highlight certain musical performance relationships, for example the performance differences between the physical characteristics of various bow articulations.

While much of the discussion thus far has been under the scope of informing the musician about their practice, analysis tools as described in this paper would also greatly benefit the educator. In observing the contract between teacher and student, the teacher's role is to guide and nurture the student into honing their technique. By effectively identifying the strong and weak areas of the student's practice, educators can best target and focus their limited time with their students. One exciting area to explore in the future would be combining multimodal musical performance metrics with practice content generation, an interesting concept which is now being investigated [15].

Lastly, this research presents results calculated after recordings were collected; however, these techniques are feasible in real-time. The statistical measurements and visualizations presented are computationally lightweight, and could very well run on today's computers, laptops, and other mobile devices such as the Apple iPad or iPhone. One benefit of a future real-time system would be that it creates a useful feedback loop—musicians and educators won't only be able to see performance data in between lessons, but also *during* sessions, providing dynamic information to influence practice, as it happens.

There is of course additional room to continue exploring NIMEs or hyperinstruments in the practice room, and many more families of instruments to reach. It would indeed be useful to explore string performance further, perhaps with a commercial bow sensor system such as the K-Bow [13], and on traditional instruments such as the violin or cello. One interesting approach would be to do another long-term study, alternating between practice with computer assisted metric feedback and regular practice without the feedback, ever few weeks. The Ezither was chosen for this study for a number of reasons including that we were unable to obtain the K-Bow, and because the performer who built the instrument was particularly interested in utilizing a computer assisted system for learning his new instrument (making his practice a great test-bed for the research). Furthermore, the authors are particularly interested in exploring similar metrics and visualizations not just on hyperinstruments, but also other non-acoustical interfaces and NIMEs. While exploring the data from these types of interfaces in the practice room is still relatively uncharted territory, this research hopes to show a glimpse of the exciting possibilities not only in the interesting mappings of NIMEs and hyperinstruments, but also the day-to-day practice required to become an expert performer.

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