EQUIPPING ARTIFICIAL GUITAR PLAYERS WITH BIOMECHANICAL CONSTRAINS: A CASE STUDY OF PRECISION AND SPEED

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ABSTRACT

Electronic means for generating music are often criticized for their "non-human" feeling. Models of expressive music performance have been used to alleviate this limitation by recreating human patterns found in music performance. These patterns are the outcome of both cognitive and biomechanical constrains. This paper focuses on the latter. We are interested in extracting biomechanical information from performers playing the guitar with a view on furnishing systems for expressive music performance with biomechanical constraints. For instance, patterns of the motor system can introduce human characteristics in musical performances that are not trivial to model, such as unintentional errors due to biomechanical limitations. In this paper we present the results of a task-performance-related experiment aimed at identifying biomechanical patterns of the left-hand of guitarists during chord shape performance tasks, and how they conform to common performance principles and pitfalls.

1. INTRODUCTION

The intimate relationship between musical motion and physical movements has been studied as a form of modelling music cognition and expression [12]. This approach, referred to as *kinematic* by Honing [7], focuses on patterns that are commonly found in music performance and how they conform to the laws of physical motion. Another approach to implementing systems for music performance is referred to as the *perceptual* approach. Both approaches, however, focus on establishing relationships between identifiable properties of the music score and the actual performance of the music, either at a cognitive or physical level. What is lacking at both approaches is an analysis of intentional and unintentional events in performances. They fail to address questions such as: How to differentiate intentional performance actions, which are the result of careful consideration, and unintentional performance errors, which may add to musical expression?

Hand movements, like all human movements, are subjective to biomechanical constraints, and are subjective to distortions and errors. Performers train themselves to be able to automate most of their musical movements at an unconscious level, but one should not forget that these actions are still carried out by a kinematically connected physical system [1]. Biomechanical models embodying such kinematic properties can be used to limit movement choices by avoiding movements that are impossible, such as those that take joints beyond their ranges of motion, or that demand forces that are physiologically impossible or very uncomfortable [4].

Heijink and Meulenbroek [6] conducted a behavioural study to explore the biomechanical basis of the complexity of the left-hand movement in guitar playing. Three factors were analyzed in relation to the notions of postural comfort when playing a sequence of single notes: a) the position of the left-hand on the guitar neck; b) finger span; and c) hand repositioning.

In this paper we introduce the basic components of an experiment that we have conducted to study the movements of the left-hand of guitar players. Here we expand on the work of Heijink and Meulenbroek by focusing on chords rather than single notes. The factors that we have analyzed are the precision and speed of the left-hand fingers while performing pre-determined chords-shapes.

2. EXPERIMENT

Five male right-handed guitar players, aged between 19 to 30 years old, took part in the experiment. They were popular (non-classical) guitarists with mixed musical backgrounds and at least 6 years of experience. The data sets of two of them were later discarded due the excessive number of procedural errors.

The instrument used was the guitar-like MIDI controller, Yamaha EZ-AG. The interfret distance in the Yamaha EZ-AG simulates the dimensions of real guitar, becoming smaller towards the body. Instead of strings, the controller has buttons on the fretboard that trigger MIDI SysEx messages identifying the buttons that have been pressed. The controller was plugged into a computer running a custom-written MIDI recorder integrated with the algorithms that analyse and store the data in a Microsoft Excel compatible file. It is a well-known phenomenon that people are poor at remembering movements, but good at remembering positions. Heijink and Meulenbroek [10] demonstrated this implicitly when their subjects preferred familiar positions on the guitar neck rather than fingering. In the context of our experiment, positions of the left-hand are regarded as chord-shapes.

When someone learns to play the guitar, hand movements and positions are stored in the brain in the form of conditional reflexes that are triggered without conscious control. Although the process of learning performance skills is often steady and incremental, the brain does not seem to store all positions of the hand explicitly. Instead, it stores a few postures and derives new postures from these representations [14]. Therefore, we decided to select chord-shapes that are often used in the first stages of learning to play the guitar, which were likely to be highly familiar to the subjects (Figure 1). This was aimed at reducing the level of cognitive activity involved in the task.

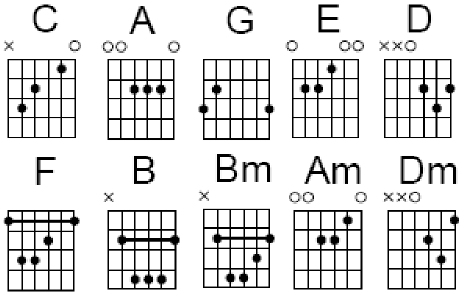

Figure 1: Chord shapes used in the experiment.

The subjects were instructed to perform the chord-shapes along the entire extension of the fretboard within frames that go from frets [1..4] up to [9..12] (Figure 2). In order to establish a common ground for comparison between the subjects, we established reference places where the hand must have been positioned before the chord was performed. These references were located at both bottom and top "strings" of the instrument. Each finger pressed and held one of the positions <string, fret> of the reference as Figure 2 shows. The measured speed of the chord-shape performance was the time elapsed from the moment where the last reference was released up to the moment where all the positions of the chord shape were pressed.

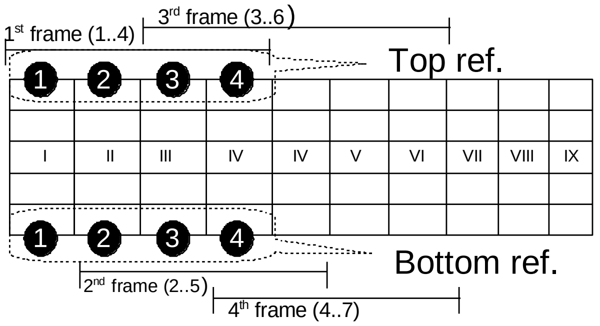

Figure 2: Frames of Reference.

To begin with, the subjects were given an exercise to warm up their fingers and adapt them to the instrument. The experimenter asked them to set the bottom reference at the frame [1..4] and "jump" to the chord shape as fast and precise as they could using any fingering they wished. Only the left-hand was used and the procedure was repeated until frame [9..12] was reached. This task was repeated for all 10 chord-shapes, from the bottom, and top references were individually recorded in the following order: C, A, G, E, D, Am, Dm, F, B, and Bm. The subjects were given the opportunity to practice the task at will before that actual recording. The data sets were analyzed while the subjects waited and they were asked to repeat those tasks that were not performed satisfactorily.

3. ANALYSIS AND RESULTS

The overall speed of the chord shape, the speed of each finger and the errors in the execution were computed. The speed was calculated by subtracting the time of the last note of the chord, through the respective button ON time, by the last reference OFF time. This task was not trivial. For instance, if a note of the chord was not played, then the speed for that chord-shape could not be determined precisely. These complications created constant outliers. In order to eliminate them, the median speed of the chord shape per reference was used to determine the mean of the chord shape speed per subject. The overall speed of the chord shape was calculated as the mean of the chord shape speed for all three subjects. The same rationale was used to calculate the speed of the fingers. In general, the bar chords took longer to be performed (Figure 3). This might be related to the number of digits involved in the task and the use of the little finger (the 4^{th} finger), which was less accurate and less strong than the others [4].

The G chord also figured between the slowest ones, reinforcing the idea that the little finger may have been slowing down the whole performance of the chord. Subjects 1 and 3 were significantly slower than Subject 2 in performing the G chord. Subjects 1 and 3 were using the little finger in the position <1,3> as opposed to Subject 3, who preferred to use the ring finger (the 3^{rd} finger) instead. Indeed, in the measurements of the speed per finger, the little finger was also the slower one (Figure 4). Interestingly, the ring finger has shown similar values for all subjects and it was the fastest finger for Subjects 1 and 3.

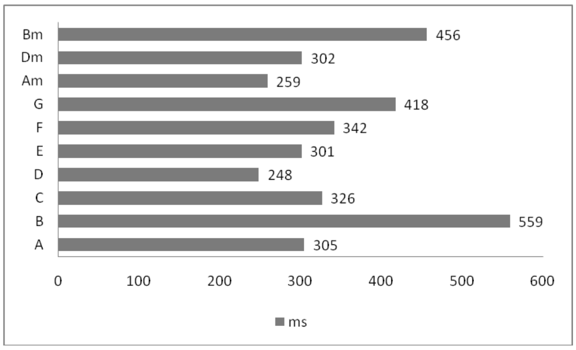

Figure 3: Chord shapes speed average.

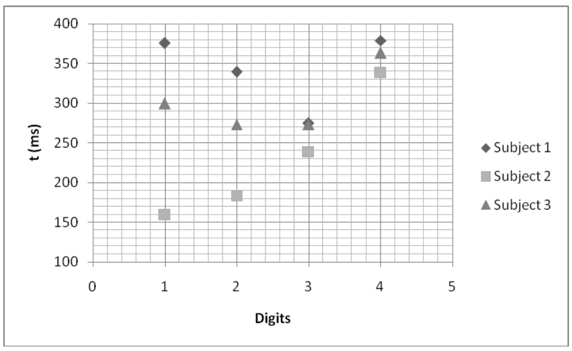

Figure 4: Average speed per finger.

The average time for the subjects to perform a chord was around 350ms. The time to perform a chord-shape can be decomposed into: a) Reaction Rime (RT), which

is the time it takes to configure and position the hand to perform the chord; and b) First-To-Last note time interval (FTL), which is the time elapsed between the first and last finger being in place.
The FTL is an interesting measure here because it can reveal trends in the use of the fingers. If the FTL time is small in comparison to the overall execution time, then the fingers may have been working together to press the buttons as a block. Conversely, if the FTL time is a large value then a finger may have been used as a guide to set local reference to the others (Figure 5).

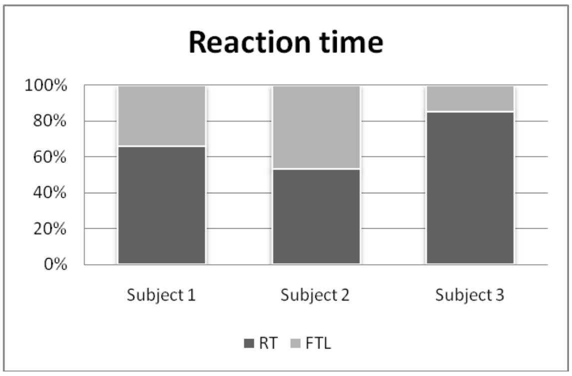

Figure 5: RT vs. FTL.

Figures 6 and 7 show the percentage of the fingers that first arrived in place for Subject 3 and 2, respectively. Note that while Subject 3 alternated the index, middle and ringer fingers as the guide, Subject 2 was much more consistent in the use of the index finger to guide the others. Unexpected, however, was the case of Subject 1 who also used the little finger as the guide in all instances of the G chord, even though he used predominately the ring and middle fingers as guide.

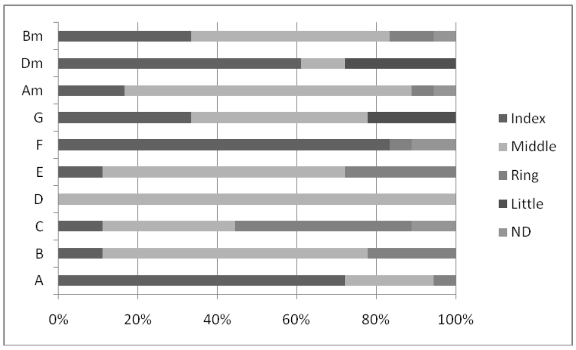

Figure 6: Guide fingers of Subject 3.

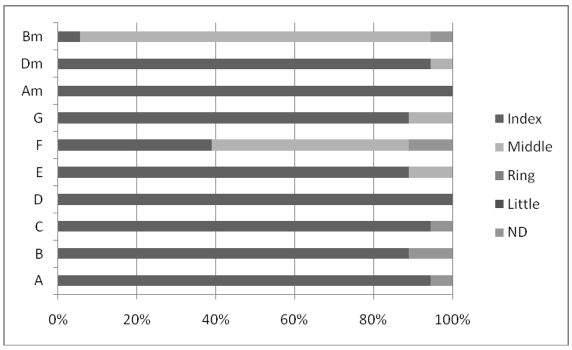

Figure 7: Guide fingers of Subject 2.

A variation in speed was also detected in different regions of the fretboard. Figure 8 maps the average speed of the performed chord per subject onto respective fretboard regions. The speed increased around the 5th fret. The 5th fret is located in the middle of the neck of the guitar, where the forearm aligns with the upper arm and shoulder; in this case the guitar is placed on the non-crossed right leg.

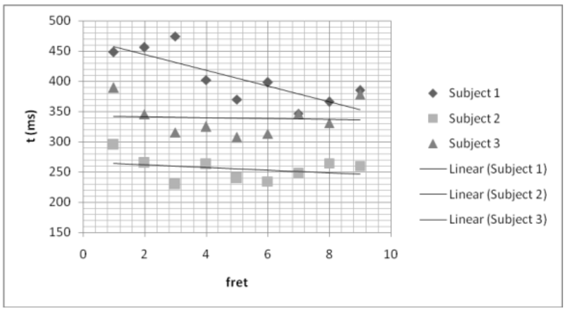

Figure 8: Chord shapes' speed rate along the fretboard,

There is a trade-off to be considered between speed, distance and precision [5]. These correlations were studied by Fitts [3] and formalized in what is known as Fitt's Law, which says that faster movements are less precise. Indeed, our experiments showed that the least precise subject was also the fastest (Figure 9).

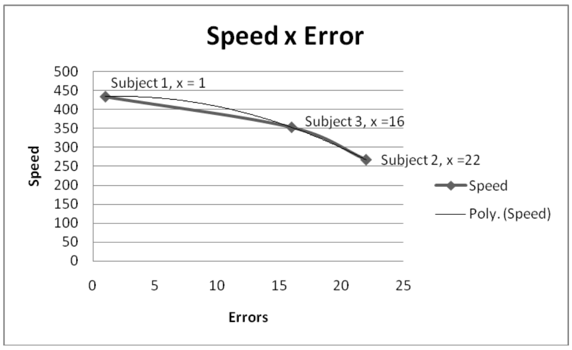

Figure 9: Performer's speed vs. Errors.

It is well established that acquiring bar techniques is a difficult stage in learning to play the guitar. The strings dig into the joints and the softer parts of the first finger causing discomfort [2]. But the discomfort is not the only factor that causes errors: the instrument we used had no strings and yet the errors only happened during the bar chords (F, B and Bm) performance. From the total of errors, 51% of them were generated by playing the B chord, followed by Bm and F with 41% and 8% respectively. The B chord is not only the slower to be played, but also is the most difficult to play.

We also analysed the quality of the errors. We classified the errors by the zone where they occurred in relation to the target as shown in Table 1, where [S] stands for string and [F] for fret. For instance, suppose that the target is the position <2, 3>. If the finger hits the positions <3, 3> and <2, 3> at the same time, then there is an error [S+]. If there is no hit for a particular position, then there is an error [N-].

S+F-	S+	SF+
F-	TARGET	F+
SF-	S-	S-F+

Table 1: Errors Zone.

Overall, the index finger was responsible for 43% of the errors, followed by the middle, little and ring fingers with 28%, 10%, and 2%, respectively. It is important to remember that these errors were related to bar-chords. Therefore the index finger was the most stressed, having to press 5 or 6 buttons at the same time. Figure 10 gives an idea of the influence of each finger in relation to the 3 most common errors. Analyzing the percentages, a pattern of the errors can be drawn. For example: Most of the [N-] errors were caused by the little finger; most of the [F-] errors were caused by the middle finger and most of the [S+] errors were caused by the ring finger.

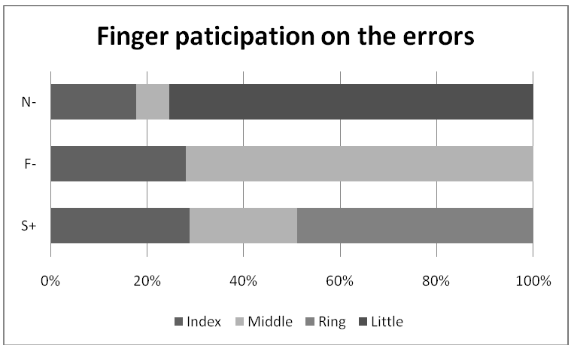

Figure 10: Fingers' contribution to the errors.

4. CONCLUDING DISCUSSION

In summary, our experiment revealed that patterns of left-hand usage in guitar playing can indeed be identified systematically.

The D chord was the fastest to be performed and the B was the slowest, taking more than twice as the D chord. In general, chord shapes that made use of the little finger had a tendency to be slower. The little finger was the slowest finger, taking an average to 360ms to reach its target. Although the ring finger is not the strongest or the most precise one, in our experiments, it was the fastest finger, taking 262ms to reach the target. Patterns of speed could be found in all three subjects, the same cannot be said in relation to their strategy in the use of the fingers. While Subject 2 made constant use of the index finger as a guide, Subject 3 preferred to group his fingers before positioning them. Trends of errors were also analyzed. Only bar chords presented errors. The index finger was responsible most of the time for these errors.

The next phase of our research is to build an artificial motor system that will be able to learn patterns of motor control for musical performance from data collected during experiments such as the one introduced above. The pressing question is how the data gathered from such experiments can be used to train the system.

Various approaches have been proposed. Radicioni and Lombardo [10] has implemented a fingering model as a graph search problem, where the cost transition between vertices were given by equations expressing biomechanical difficulties. The principle of mechanical difficulty has also been used by Radisavljevic and Driessen [11] in a dynamic programming (DP) approach to find the optimal fingering sequence. Tuohy and Potter [13] used artificial neural networks (ANN) to model the guitar fingering strategies.

Working with biological data, Iberall [8, 9] was one of the first to use ANN to plan hand configurations. Uno et al. [20] also used ANN to determine optimal hand-shapes combining visual and somatosensory information. Following the work of Iberall et al. and Uno et al. we are currently testing a number of ANN architectures to assess their ability to determine correlations of the most relevant biomechanical attributes involved in a guitar performance and predict performance errors.

5. REFERENCES

[1] Altenmuller, E.W., M. and Kesselring, J. *Music, Motor Control, and the Brain* Oxford, Oxford University Press, 2006.

[2] Chapman, R. *The Complete Guitarist*, Dorling Kindersley, 1993.

[3] Fitts, P.M. "The information capacity of the human motor system in controlling the amplitude of movement", *J. Exp. PsychoL, 47* (6) 381–381, 1954.

[4] Freivalds, A. *Biomechanics of the Upper Limbs: Mechanics, Modeling, and Musculoskeletal Injuries*, CRC Press, 2004.

[5] Grandjean, E. *Fitting the task to the man*. New York, Taylor and Francis, 1988.

[6] Heijink, H. and Meulenbroek, R.G. "On the complexity of classical guitar playing: functional adaptations to task constraints", *J Mot Behav, 34* (4) 339--351, 2002.

[7] Honing, H. *Computational Modeling of Music Cognition: A Case Study on Model Selection*, Univ. of California Press, 2004.

[8] Iberall, T. A neural network for planning hand shapes in human prehension *Proceedings of the Automation and Controls Conference*, pp. 2288–2293 1988.

[9] Iberall, T. and Fagg, A.H. "Neural network models for selecting hand shapes", *Hand and brain. Academic Press, San Diego* 243--264, 1996.

[10] Radicioni, D. and Lombardo, V., "Guitar Fingering for Music Performance". in *Proc. International Computer Music Conference*, Spain, 2005.

[11] Radisavljevic, A. and Driessen, P. "Path Difference Learning for Guitar Fingering Problem", *Proceedings of the International Computer Music Conference*, 2004.

[12] Todd, N.P.M.A. "The kinematics of musical expression", *The Journal of the Acoustical Society of America, 97* 1940, 1995.

[13] Tuohy, D.R.P., W. D., "An Evolved Neural Network/HC Hybrid for Tablature Creation in GA-based Guitar Arranging". in *Proceeding of the International Computer Music Conference* New Orleans, Louisiana, 2006.

[14] Wing, A.M., Haggard, P. and Flanagan, J.R. *Hand and brain: the neurophysiology and psychology of hand movements*, Academic Press San Diego, 1996.