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Understanding Biomechanical Constraints for Modelling Expressive UbiMus Performance: A Guitar Case Study

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Understanding Biomechanical Constraints for Modelling Expressive UbiMus Performance: A Guitar Case Study

Computer-generated musical performances – even in a ubimus context - are often criticized for being unable to match the expressivity found in performances by humans. Two approaches have been often adopted to research into modelling expressive music performance on computers. The first focuses on sound; that is, on modelling patterns of deviations between a recorded human performance and the music score. The second focuses on modelling the cognitive processes involved in a musical performance. Both approaches are valid and can complement each other. In this paper, we discuss the role of errors when modelling expressive music performance, which concerns the physical manipulation of the instrument by the performer. In addition, a study on the motor and biomechanical processes of the guitar performance is presented. Some findings on the speed, precision, and force of a guitarist´s left-hand are presented overarching questions regarded to the way a human body performs actions when playing the guitar, and the possibility to err in such context.

Keywords: expressive music performance, biomechanical modelling, guitar performance; ubimus

1. Introduction

Musical performance provides a rich domain for the study of both cognitive and motor skills (Palmer, 1997). In Western tonal music, it is typically a means of communication involving three actors: the composer, the performer, and the listener (De Poli, 2004). The composer codifies musical ideas into a written notation (score); the performer transforms the score into an acoustic signal; and the listeners decode the acoustic signal back into ideas (Kendall & Carterette, 1990). Sometimes the role of these actors is not exactly this way: for example, in a free jazz improvisation the composer and the interpreter overlap. However, it is generally accepted that a performer enables the communication of such ideas between composer and listener at performance time.

The vast majority of contemporary research on musical performance has focused on perceptual processes of the listener since this is the focus of all musical activity (Sloboda, 2000), after all, composition would have no purpose if it were not experienced. The composer's part, the score, has long been studied and scrutinized in terms of its structural aspects such as harmony, melody, form, and instrumentation, as well as studying the composer's intention or the inherent emotional expression (Friberg, 2006). However, the key in modelling music performance lies with the performer.

The performer interprets the symbolic information on the score and produces the sound by using a musical instrument (Mion & De Poli, 2004). The performing artist is an indispensable part of the communication process, shaping the music in creative ways by continually varying parameters like tempo, timing, dynamics (loudness), and articulation, in order to express a personal understanding of the music (Madsen & Widmer, 2006).

To model music performance we must first understand the processes the performer carries out in order to 'interpret' the piece of music. Only then it will be possible to artificially recreate this 'interpretational' behaviour. Two main approaches have been taken in attempting to do this:

(1) The first approach simply focuses on the outcome, the produced music, searching for patterns of deviations between the information the performer is given (the musical score) and the performance that is produced. The internal processes of performer are not relevant and we will refer to this approach as Psycho-Acoustics-Based Modelling;
(2) The second approach is concerned with the internal processes of the performer, focusing on the source, the causal phenomena of the sound, such as instrument control. It attempts to understand the reasoning behind the performance actions either on a cognitive, physiological, or biomechanical level. This too searches for pattern, however focuses on behavioural patterns. This second approach will be referred as Performer-Based Modelling.

In this paper, these two approaches are briefly discussed but more emphasis is given on Performer-Based Modelling, pointing out the importance of behavioural-based models, in particular on biomechanical models. Our idea is that physical manipulation of an instrument by the performer is often neglected in previous research

We present the findings of an ergonomic study of the guitar with estimation of forces needed to play correctly clean notes and chords, and a biomechanical study of errors made by guitar players. Some findings of experiments regarded to speed, force and precision of the guitarist left-hand are thus presented as well as results from an analysis of guitar performance errors. Combined, these results provide important insights for the development Expressive Music Performance Models, specifically for guitar performance. In our point of view, such comprehension is essential for better proposing Digital Musical Instruments and EMP systems in line with ubimus concepts, specially improving the musical design interaction for non-musicians as discussed after this introduction. The sections 3 and 4 respectively presents psycho-acoustics-based modeling and performer-based modeling approaches to model music performance. Section 5 discusses the role of errors in a music performance, which concerns the physical manipulation of an instrument by the performer. Section 6, 7 and 8 in dedicated the study of the guitar playing, respectively studding the ergonomics of the guitar, the biomechanics of the guitar players, and the pattern of performance errors found within this interaction. Section 9 presents the final considerations.

2. A Biomechanical Approach to UbiMus Tools

We have proposed the adoption of the term Ubiuitous Music (Keller, Flores, Pimenta, Capasso, & Tinajero, 2011; Keller, Lazzarini, & Pimenta, 2014) - or simply Ubimus - to promote practices that empower participants of musical experiences through socially oriented, creativity-enhancing tools (Keller et al., 2015). To achieve this goal, our group has been engaged in a multidisciplinary effort to investigate the creative potential of converging forms of social interaction, mobile and distributed technologies and innovative music-making practices. One of our goals is to develop tools which take advantage of these inclusive contexts, providing conditions to novices to participate in creative activities, ideally in any place and at any moment. One approach for this relies on repurposing everyday consumer mobile devices (devices they already own, and are familiar with) as ubiquitous music interfaces for use in musical activities, taking benefit from their distinctive capabilities of portability, mobility, and connectivity and above all from their availability to the average person (including novices in music). In this paper we take a rather different approach by investigating how the human body fits the task to manipulate a musical instrument in order to propose more intuitive, safer, comfortable interaction to music making. If Ubimus is indeed concern with the availability of its musical instruments to non-musicians, the findings reported by this paper must be in centre of the design of those.

Digital Musical Instruments (DMIs), including those created within the ubimus paradigm, has been created disregarding the human motor abilities to deal with it. It is true that musical instruments (acoustic and digital) have evolved to provide a better fit to our body, even if it is still far from the ideal. Ergonomically-wise, musical instruments rarely change. For example, take one of the first musical instruments ever found: a bone flute (41000 BCE). Sumerians and Egyptians (3000 BCE) improved its design by adding three or four finger-holes to their bamboo flutes. The Ancient Greeks (800 BCE), who also had quite sophisticated flutes, blown at the open upper end and had six fingerholes. Romans (200 BCE) used traverse (side-blow, flute). Finally, the modern flute design was pretty much proposed in 1847 by Theobald Boehm: an improved flute with cylindrical tubing and a parabolically conical headjoint. Felt pads were added to the key cups to prevent the escape of air. The shape of the embouchure changed, which hitherto had been oval or round, to a rectangle with rounded corners. The material he chose was German silver, to which he ascribed the best acoustic properties (Sachs, 2006). One can argue that the Boehm is a great improvement over the bone flute, but the interaction design is the same: blow through a hole, stop the air from escaping with the fingers (or equivalent), and make the air vibrates producing the sound. This design makes sense because, presumably, we (humans) are good at controlling our breath and we can do that without compromising our fine motor skill, therefore we can block the holes of the flute with our fingers while we still control our breath. Surely it is a proven design but how good are we really in making music using such design pattern and what are the consequences in doing so? Using and respiratory system to make music will introduce constraints in the musical performance granting its distinctive aesthetics. It does makes sense biomechanically-wise since it is a simple mechanism in which humans can effectively shape the sound (the air) and get a responsive haptic feed-back. That said, if you have the chance to build a flute from scratch, in line with the ubimus key concepts, would you follow the same interaction design?

Developing musical interaction is a complex and multidisciplinary task with some very interesting challenges. On a high level, these can be divided into two classes: a) Technology-related challenges; and b) Human-related challenges. Some examples of the first class include studying sensors required in ubicomp, building system software for interoperability and integration, and researching mobile ad hoc networking. As for the latter class, some examples include studying smart home usability, and tools for performing such studies. In this paper we focus on the class of human-related challenges by investigating the ergonomics and biomechanics aspects of a guitar performance. The reported findings can indeed contribute to the design of new ubimus DMI's that are inspired in the same interaction pattern used in guitar playing (i.e. string manipulation). Moreover, this is done without disregarding the expressive aspect of musical performance that must be embedded in such technology.

3. Psycho-Acoustics-Based Modelling

Structure-expression relationships have been formalized in computational models that apply rules to input structural descriptions of musical scores (Sundberg, 2003). In fact, measuring the deviation of the music performance from what is actually written in the score is the most common technique to quantify the 'expressiveness' of the performance.

Extensive work has been developed to identify relevant cues for musical expression in audio signals and then, with the aid of score-matching algorithms, compare them with the notated score. Such cues include: tempo, sound level, timing, intonation, articulation, timbre, vibrato, tone attacks, tone decays and pauses (Poepel, 2005). This approach is referred to as analysis-by-synthesis and it typically starts with a hypothesized principle, realizes it in terms of a synthetic performance, and evaluates it by listening. If needed, the hypothesized principle is further modified and the process repeated (Sundberg, Askenfelt, Fryden 1983).

Another approach referred to as analysis-by-measurement takes empirical evidence directly from measurements of human expressive performances. Both approaches use the musical notation (score) as a reference to quantify deviations.

Whatever the source of the data, some computational techniques have been recurrently used in an attempt to model an expressive performance. These models serve to generalise the findings and have both a descriptive and predictive value (Widmer, 2004). Some of these techniques and models are: Rule-Based approach (Gilden, 2001) , Mathematical Approach (Mazzola, 2002), Machine Learning Approach (Madsen & Widmer, 2006). However, since we are interested in isolating unintentional from the intentional actions that the performer executes, none of those approaches will be further discussed in this paper.

4. Performer-Based Modelling

The act of interpreting, structuring, and physically realizing a piece of music is a complex human activity with many facets – physical, acoustic, physiological, psychological, social, and artistic (Widmer, 2004).

According to Juslin (2003), performance expression is best conceptualized as a multi-dimensional phenomenon consisting of five primary components:

(1) Generative rules;
(2) Emotional expression;
(3) Motion principles;
(4) Stylistic unintended local deviations; and
(5) Random variations.

From these five components listed by Juslin (2003), the first one – generative rules - can be investigated using simulation-based approaches related to Psycho-Acoustics-Based Modelling . To investigate the other four topics, a multi-disciplinary approach is required, typically involving areas such as psychology, musicology, and biomechanics. As a consequence, computational models of music performance are often used for evaluation goals (usually to validate cognitive theories) rather than for predictive goals.

4.1 (Hidden) Musical Structure Models

Many findings have established a causal relationship between musical structure and patterns of performance expression (Clarke, 1988).

The notated music score is just a small part of the actual music. Not every intended nuance can be captured in the formalism of a written musical notation (Widmer, 2004). Performers must not only decode the symbolic information written in the music score but also interpret its 'hidden' structural content in order to adequately communicate the composer's ideas to the listener (Drake & Palmer, 1993). One of the most well documented relationships is the marking of group boundaries, especially phrases, with decreases in tempo and dynamics (Henderson, 1936).

Bean (1939) however, pointed out a human characteristic acting upon the segmentation strategy: short-term memory capacity. Good sight-readers work with effective chunking (of the score) using short-term memory (Gabrielsson, 1999). Sight reading is especially important in the first stage of the performance plan, that is acquiring knowledge of the music and developing preliminary ideas about how it should be performed. According to Gabrielsson (1999), it is also in this first stage that the structural analysis reveals the real meaning of the musical information. The final version of the performance is what the musician intends to replicate in front of the live audience. In order to investigate how the audience could be able to perceive the expression in this performance, perceptual models are usually adopted.

4.2 Perceptual Models

Since the rise of experimental psychology in the 19th century, psychology's understanding of perception has progressed by combining a variety of principles, theories, models and techniques. Perception has been studied and found in several domains of cognition, including speech (Perkell & Klatt, 1986), motor behaviour (Heuer, 1991) and object motion (Shepard, 2002). It has also been the topic of several studies in music perception. More than an ability to perceive sounds by detecting vibrations, music perception aims to explain and understand musical behaviour and experience, including the processes through which music is perceived, shifting the focus from the study of isolated sounds and elements to the perception of their inter-relationships and human reactions to them. A perceptual model helps to predict the degree of expressive freedom a performer has in a music performance before the listener perceives a misinterpretation.

These models attempt to predict when, for example, the rhythm performed with some tempo and timing variations will still be recognizable as such by the listener. Pisoni (1977) found listeners to be able to distinguish temporal differences between two successive acoustic events (typically pure tones) between 500 Hz and 1.500 Hz signal at a minimum relative of 20 ms. Moore et. al. (1993) found that the ability of listeners to detect gaps in a signal was around 6 to 8 ms for signals in the range of 400 to 2.000 Hz.

Whilst the technical component of a skilled music performance is related to the mechanisms of producing fluent outputs, the expressive component is derived from intentional variations in performance parameters chosen by the performer to influence the cognitive and aesthetic effect on the listener (Palmer, 1997). A performer's intentional deviations generally correspond to change in the produced sound (e.g., changes of dynamics, tempo, articulation, and so on) that even non-musical listeners can perceive fairly well, even when underlying acoustic changes are not identifiable (Palmer, 1997).

Perceptual models have been the preferred approach to model expressive timing in music performance (Honing, 2006) but this is not the only way to do it. In addition to Perceptual Models, Kinematic Models have also been used in the domain of music cognition. The latter advocates an intimate relationship between musical motion and physical movement.

4.3 Kinematic Models

The relationship between musical motion and physical movements has been studied as a form of modelling music cognition and expression (Todd, 1995). It focuses on the identification of patterns that are commonly found in music performance, and establishes how these patterns conform to the laws of physical motion. In order to sound natural in performance, expressive timing must conform to the principle of human movement (Honing, 2006) that is based on an internal sense of motion.

This principle reflects upon the notion that music performance and perception have their origins in the kinematic and dynamic characteristics of typical motor actions. For example, regularities observed in a sequence of foot movements during walking or running are similar to regularities observed in sequences of beats or note values when a musical performance changes tempo.

An underlying principle of this school of thinking is that we (humans) experience and make sense of musical phenomena by metaphorically mapping the concepts derived from our bodily experience of the physical world into music. Accordingly, listeners hear the unfolding musical events as shaped by the action of certain musical forces that behave similarly to the forces behind our movements in the physical world such as gravity and inertia (Dogantan-Dack, 2006). Baily (1985) even argues that the performer’s internal representation of music is in terms of movement, rather than sound.

Arguments against kinematic models suggest that physical notions of energy cannot be equated with psychological concepts of musical energy. Another criticism of the kinematic models is that they are insensitive of rhythmic structure of the musical material. There is no enough evidence to stablish correspondence between the rules that cope with human motion and kinematical models of expressive timing (Honing, 2006).

4.4 Internal Time-keeping System (Motor Control) Models

In a music performance, the motor system of the performer assumes the role of planning the sequencing of movements to play a musical instrument on the basis of his or her internal body clock. The primary role of such internal clock is to regulate and coordinate complex time series such as those produced between hands (Povel & Essens, 1985) but it also acts as timekeeper by controlling the time scale of movement trajectories (Shaffer, 1981).

Fraises (1982) suggests that our internal clock operates at 600 ms at the level of tactus. For instance, people often generate beat patterns around 600 ms in spontaneous rhythmic tapping tasks. Time periods greater than or less than this primary timing level are achieved by concatenating or dividing beat periods (Shaffer, 1981).

Naturally, most models based on internal-clocks represent at metrical level a musical sequence (Parncutt, Sloboda, Clarke, Raekallio, & Desain, 1997). For instance, timing of musical notes in a piece changes according to different tempi in motor exercises as Gabrielsson (1999) reported:

(1) Faster or slower tempi present a higher variability of inter-note intervals than intermediate tempo;
(2) The velocity of the key-press (piano) increases with tempo;
(3) Left and right hands present different key-press (piano) velocities, note durations, and overlap between consecutive notes.

Performance timing can also exhibit stability at more abstract hierarchical levels, such as entire musical pieces. The standard deviation of the total piece (35-40 min) duration is about 1% smaller than that of individual movements within the piece (Palmer, 1997). In simple terms, if one movement is shortened, another compensates in duration, which suggests temporal control at a level higher than the individual movements.

Motor control is responsible for planning and synchronizing the movements of the musician but when it comes to physically performing the movement, biomechanical constraints take over. It is due to the muscles, joints and tendons that the performer is most exposed to failures and breakdowns either caused by internal (e.g. fatigue) or external (e.g. temperature) factors.

4.5 Biomechanical Models

Psychological studies of music performance have provided a wealth of information on musical expression and its relationship with the structure of a piece. However, these studies have largely ignored the physical manipulation of the instrument by the performer, even though the mechanics of the performer's body is assumed to play a decisive role in shaping the sound (Sundberg, 2000).

Performance is traditionally the means through which works of music reach audiences, and it is performance that makes the physicality of the body behind the music immediately evident to listeners (Dogantan-Dack, 2006). Yet, it is not common for music performance models to consider biomechanical constraints in the generation of music performances.

More often biomechanical models are used in the understanding and prevention of possible injuries resultant of the accumulation of micro traumas when the human physiological limits are exceeded, a common problem for musicians (Ericsson, 1993). Nevertheless, Parncutt (1997) did use of biomechanical findings extracted from the literature to establish a set of rules that would find the most suitable fingering within a particular musical context in a piano performance. Parncutt's rules considered the stretch of the fingers, displacements, the use of weak fingers (4 and 5) and the thumb.

Although Parncutt's model can predict some of the fingering choices and avoidances when confronted to the fingering preferences of human pianists, his results are questionable because his model ignored crucial cognitive aspects, such as the use of common fingerings for scales and arpeggio, register and style. More recently, Jacobs (2001) identified a number of drawbacks in Parncutt's model and successfully proposed some refinements, most of which were related to the weak-finger rules and a new scoring system based on physical distance range.

Heijink and Meulenbroek (2002) also 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; c) hand repositioning; Their study protocol resorted in a performance-related definition of travel-cost of a movement, proposed by Rosenbaum (1996), which assumes that a guitarist is likely to choose the fingering that requires the least amount of physical effort when no other overriding cognitive or musical constraints need to be taken into account. A similar approach has been previously tested in an agent-based guitar performance system (Costalonga et al. 2008). In either case, it was found that biomechanical factors played a secondary role in the performer's choice of fingerings. Indeed, biomechanical constrains do limit the available options of possible fingerings, however musical style, personal preference, and other cognitive factors are more pertinent than biomechanical, as also observed by (Heijink and Meulenbroek 2002).

5. The Role of Errors in a Music Performance

Performers have an impressive ability to replicate the expressive profile of a piece in performance, with a degree of variability in the timing properties of a performance of one percent or less (Clarke, 1988). However, even expert performers will eventually err for variety of reasons (Palmer, 1997).

Deviations from the musical notation are expected in Western classical music as part of a performer's artistic license, and it is often difficult to distinguish these artistic deviations from actual errors (Palmer, 1997). In fact, errors can lead to unexpected musical discoveries that ultimately improve the performer's technique and, as a result, enrich the performance; this effect is known as serendipity.

The problem of distinguishing deviation from errors was first noted by Desain et al. (1997) while he was attempting to produce a more robust score-matching algorithm. He mentioned three situations that led score-matching algorithms to perform poorly:

(1) There may be events in the score that are not written out completely (e.g., certain kinds of ornaments);
(2) In the case of parallel voices, expressive timing may cause the order of events in the performance to be different from the order specified in the score;
(3) Finally, the performer could omit, insert or change notes by mistake, often resulting in many alternative interpretations, especially in the case of repeated notes of the same pitch.

As Desain (1997) observed, performers never play equally. In all human performance tasks, errors seem to be a frequent occurrence and they come from different sources: cognitive, motor or mechanical (Drake & Palmer, 1993).

Although errors are a frequent occurrence in music performance, there is little documented evidence of this. Perhaps the most influential study of error in music performance is the work of Palmer and Van de Sande (1993). Nevertheless, it is a study of psychology that aims to investigate cognitive plans of music performance; for that reason, motor and biomechanical constraints are not contemplated.

According to Wickens and Hollands (2000), errors can be classified as: mistakes, slips and lapses. In summary, errors of interpretation or of the choice of meaning are called mistakes and originate from cognitive processes. Slips are quite different from mistakes, in a slip the understanding of the situation is correct and the correct intention is formulated, but the wrong action is accidentally triggered due to a motor or biomechanical problem. Lapses overlap these categories; they are the failure to perform an action when a procedural step is missing which could originate at the cognitive, motor or mechanical level.

In the field of psychology there is a belief that errors in skilled performance arise due to multiple internal representations of the desired behaviour (Norman, 1981). Articulatory properties (motor commands produced for a specified sequence of successive events) are believed to be a secondary cause in error production, merely influencing performance plans. Nevertheless, it is acknowledged that the mental plans underlying music performance must also consider constraints related to sound production using a musical instrument in addition to perceptual constraints. For instance, keyboard performances of musical scales suggest a greater range of articulatory control for the right hand than for the left hand (MacKenzie & Van Eerd, 1990).

In their investigation of the cognitive errors in music performance, Palmer and Van de Sande(1993) adopted a similar error coding scheme to that used in speech error research (Dell, 1986) adapted for the musical domain. The classification only considered pitch errors surrounded in a musical context or not. The error types were: note addition, note deletion, note substitution, and note shift. A substitution involves a note event replacing a target; an addition involves a note event being added (without replacing a target); a deletion involves a target being deleted; and a shift involves the movement of a target to a neighbouring location. Finally, contextual errors can reflect the range of influence of different plans in the type of movement, including forward movement (an event performed too early; anticipations), backward movement (an event performed too late; perseverations), or both (events switching neighbouring locations; exchanges).

The results reported by Palmer and Van de Sande (1993) show that most errors (98%) involved one size unit (chord or note) and most errors (91%) involved single-notes (whether from part of a chord or from a solitary notated event). Contextual errors made up 57% of the total errors, the greatest percentages of which were substitutions (31%) and contextual deletions (deletion of a repeating pitch, 31%). Of the movement errors (substitutions, additions, and shifts, which comprised 69% of the contextual errors), forward (early) movement was most frequent (52%), backward (late) movement second most frequent (37%), and bidirectional movement (exchanges) least frequent (11%).

The 'production errors', as referred by Palmer and Van de Sande (1993) indicated different influences of conceptual (melody interpretation), compositional (across- and within-voice associations), and articulatory processes (hand and finger movements) in planning music performance. In addition, the size, harmonic dimension and diatonic dimension of production errors suggest that retrieval of musical elements from memory reflects multiple structural levels and units.

Palmer and Van de Sande (1993) also reported that articulatory advantages are independent of conceptual processes of interpretation. Evidence shows reduced likelihood of error in the highest frequency voice, which are normally controlled by outer right-hand fingers; the authors accredited this fact to a consistent and well-learned mapping of the melody to outer right-hand finger movements in keyboard performance. Nevertheless, the authors also acknowledge to ergonomic and biomechanical implications in such behaviour. Bare in mind that, before the birth of human factors or ergonomics, emphasis was placed on 'designing the human to fit the machine' (Wickens & Hollands, 2000). Therefore, it is not unusual to find performers contorting themselves around musical instruments that were designed in the last century, when ergonomics and human factors were not formally taken into consideration when building a musical instrument.

Researchers working in the fields of Ergonomics and Human Factors have been working to understand the limitation of human abilities independently of its source, be that cognitive, motor, or biomechanical. The fundamental goal is to reduce error, increase productivity, and enhance safety and comfort when the human interacts with an artefact or system (Wickens & Hollands, 2000). Despite the extensive research that has been done to understand the causes of errors at the cognitive, motor and mechanical level, only a handful of studies have addressed music performance. Conversely, most of the motor control studies in music performance do recognize the relevance of the error (Juslin, Friberg, & Bresin, 2002; Sloboda, 2000) In order to exemplify the relevance that errors might have in a music performance context we can compare it with the findings of a similar motor task: typing in a word processor. The human error probability (HEP) is the basic unit of human reliability in discrete tasks and it is estimated from the ratio of errors committed to the total number of opportunities for that error (Freivalds, 2004).

Card and colleagues (1983) estimated that the typists make mistakes or choose inefficient commands on 30% HEP.

The challenge is to establish when errors are caused by cognitive processes and when they are caused by mechanical and motor limitations of the body. Is the music piece demanding more than is humanly possible? If so, what are the consequences?

6. An Ergonomic Study of the Guitar

A guitar can be classified by its acoustics, playability, fitness and aesthetics. Playability (or responsiveness) and fitness are interlinked parameters, and they are the focus of our investigation.

Playability determines how much effort is required to achieve clear, well-formed individual notes, particularly during rapid and difficult passages. Fitness focuses on how well the instrument suits the performer's characteristics to improve the instrument playability. The acoustic properties of guitars play a very significant role, if not the most significant, in the simulation by computers of a realistic music performance. However, the guitar's acoustic properties are not the scope of this paper, with the exception of a particular type of sound: noises.

The word 'noise' usually refers to an unwanted sound, which could arguably be considered unfair. Indeed, there is an obvious relationship between noise and error; and naturally, performers do try to avoid errors. Performance errors (slips) most certainly terminate in one of another form of noise. However, we believe that is through the perception of the noise that the audience identifies the imperfect human nature behind music performance; thus, noises should also be part of a computer-generated performance; but not all types of noises are useful. It is important to establish the right balance between noises and pure sounds. It is not any 'random' noise that will produce the desired 'human-feel' in a computer-generated performance. To do so, the correlation between the specific performance errors and the noises they produce must be found.

Noise is also an important part of the sound signature of an instrument. For instance, the sound from the finger sliding along the guitar before it is plucked is very characteristic. If the finger noise is left out an important part of the tone is missing (Cuzzucoli & Lombardo, 1999).

In guitar performances, there is yet another characteristic noise caused by the fingers rubbing along the string, known as pre-scratch. Pre-scratch is a term used to refer to the sound component that precedes the actual tone. It is caused by the fingers of the right-hand rubbing along the string before it is released. In the *apoyando* and *tirandu* techniques the finger is normally placed on the strings in such a way that both the fingernail and the fingertip touch the string, producing a noise of very short duration, lasting somewhere between 1 ms and 5 ms, just long enough to be audibly detectable (Valimaki, Huopaniemi, Karjalainen, & Janosy, 1996).

The ‘finger slide’ and the ‘pre-stretches’ are the both type of noises that can be found in the modern physical modelling synthesis techniques (Cuzzucoli & Lombardo, 1999; Valimaki et al., 1996). However, in order to make these noises sound realistic in a musical context, the moment they are used needs to be carefully selected. Finding the moment when noises (or errors) are likely to happen still demands more investigation.

There are other noises, however, that have been largely ignored by most of synthesis techniques, even though they occur consistently in guitar performances. In fact, several different noises can be produced if not enough pressure is applied in order to stop the string properly. Two examples are: a) muffled/damped notes; and b) buzzed notes.

We ran an experiment that was intended to find the force boundaries needed to produce clean, buzzed, and muffled notes, with the aid of an INSTRON 5582 Universal Test Machine All the six strings of the tested guitar (Antoria Archtop Jazz Guitar equipped with a set of strings D’Addario extra-light tuned (standard) with the aid of an Intelli Chromatic Turner IMT-500) were measured in three regions of the fretboard: 1st - 3rd frets, the 5th fret; and 12th fret. The values for the other frets were interpolated. The analysis of the quality of the note generated was subjective to the personal evaluation of the experimenter.

Figure 1 shows the results of the measurement. In summary, the experiment shows that the force range required to produce clean notes on the particular guitar tested stayed between 0.204 and 0.897, with an average of 0.423 kgf; this was considerably higher than initial calculations based on string action, gauge and tension had suggested. The calculated average force required was around 0.223 kgf with [5th fret, 1st string] as the position that required the least amount of force (0.141 kgf) and [1st fret, 3rd string] as the position that required the greatest amount of force (0.438 kgf).

<<Insert Figure 1>>

Figure 1: Measured forces to produce clean notes on a real guitar. The x-axis corresponds to the fret region and y-axis the real force (kilogram force).

Normally, buzzed and muffled notes will often originate from a poor performance technique but it could also be due to a low-quality instrument. Nevertheless, we also compiled the force measurement required to produce ‘buzzed-notes’ and, as expected, they are lower than those required to produce clean notes, ranging from 0.173 to 0.611, on average 0.353 kgf or 0.100 kgf less. For this work, any force value below the recorded for a buzzed-note is treated as muffled-note, even though this might not always be the case in the reality.

<< Insert Figure 2>>

Figure 2: Calculated vs. Measured forces for string displacement. The outer circle (in blue) shows the measured force and the inner circle (in red) shows the calculated force. The fret regions are shown in the peripheral area of the chart.

The graph in Figure 2 shows the radical difference between the expected (theoretical) and the real data measurement. The blue line is the measured value and the red line is the theoretically calculated values. Note that for the sake of clarity the only representative frets for this comparison are the 1st, 2nd, 3rd, 5th and 12th. The others are interpolations. As can be observed, the difference is greater in the strings with a higher gauge. The measured values are on average 0.144 kgf higher than those calculated but most of this difference comes from the 12th fret, especially on the 4th, 5th and 6th strings.

Based on these data, it is possible to conclude that the guitar setup, maintenance, and quality of construction can indeed play a significant role in some common errors in guitar playing mainly regarded to the generation of buzzed and muffled notes. However, would a guitar player be able to adapt and overcome such unforeseen difficulties during a live performance?

7. A Biomechanical Study of Guitar Player

Normally, a musical performance is not a task that requires excessive force. In fact, in many skilled activities the skilled man is relaxed and economical in his movements, whereas the novice's work is cramped and tiring (Grandjean, 1988). Parlitz et al. (1998) have shown that amateur pianists not only use more force on every stroke but also used it for longer.

It is not in the context of this work discuss the details of the human physiology behind a musical performance. So, in summary, consider that each muscle fibre contracts with a certain force, and the strength of the whole muscle is the sum of these muscle fibres. The maximum strength of a human muscle lies between 0.3 and 0.4 N/mm^2 per the cross-section (PCSA); thus, a muscle with a cross-sectional area of 100 mm^2 can support a weight of 3-4 kg (30-40 N) (Grandjean, 1988). The main force producer muscles in the flexion of the index, middle, ring are the *Flexor Digitorum Superficialis (FDS)* and the *Flexor Digitorum Profundus (FDP).* In a pinch grip action, the tendon forces were found to be in the range of 25 to 125 N (12.74 kgf) for the FDP and 10 to 75N (7.6 kgf) for the FDS (Freivalds, 2004, p. 215). This power output is more than enough to produce clean notes on guitar (the measured force to generate clean notes on a real guitar ranged from 0.204 to 0.897 kgf). The straight forward conclusion is that, obviously, humans do have enough strength to play guitar but it does require strategy and technique in order to not err due to fatigue.

To exemplify the level of effort that can be encountered in a guitar performance, consider an F major chord executed as shown in Figure 3. If we consider the data collected from the Antoria Guitar and calculate all the force required for producing a clean note in all the positions of this chord, we would end up with the cumulative force of 2.28 kgf to perform this chord shape in the first fret. The same chord shape in the 10th fret would require a force of 3.52 kgf to be performed. Normally, an additional 10-40% of extra-force is unintentionally used as a safety margin (Wing, Haggard, & Flanagan, 1996) which would increase the force to 4.92 kgf.

<< Insert Figure 3>>

Figure 3: F (Barre) Chord Shape

A barre-chord is a type of palmar pinch grip. The average maximum force of a palmar-pinch grip of the left-hand of male adults stays around 10.4 kgf (Mathiowetz et al., 1985) hence a 47.3% MVC (Muscle Voluntary Contraction) is required to perform this chord. Danion and Galléa (2004) propose that steady force output by the fingers can only be maintained at a level 30-40% MCV, meaning that anything above this range can only be maintained for a short period of time usually bellow 6 seconds before the muscles get fatigued. So, in short, 6 second is the amount of time that an average person would be able to perform this chord-shape on the Antoria Guitar.

Now, if the primary muscles suffer fatigue, an unintended contraction of other muscles induces a change in posture to alleviate the primary fatigued muscles. This means that the task will be performed by muscles that are not the most effective to the task, inducing loss of precision and, again, increasing the risk of errors. This phenomenon is known as contralateral activation and it is more evident in highly repetitive tasks or tasks that require awkward postures, such as guitar playing.

In physiology, muscular fatigue is a phenomenon that reduces the performance of a muscle after a stress, not only reducing its power but also slowing the movement (Grandjean, 1988).

While muscle force is proportional to physiological cross-section area (PSCA), muscle speed (or excursion) is proportional to fibre length (Wing et al., 1996, p. 69). Wickiewicz, Roy, Powell and Edgerton (1983) suggests the maximum speed for contraction of human muscles is about 8 lengths/s for slow-twitch and 14 lengths/s for fast twitch. These values however need to be treated with some reservation because they were extrapolated from mixed fibre muscles experiments. The fibre type composition of the finger flexor muscles (FDP and FDS) is also mixed, with a slightly lower proportion of type I fibres (Maurer, Singer, & Schieber, 1995; Mizuno, 1994). Considering the FDP (index finger) fibre length of 61 mm (for FDS is 31 mm), a full contraction would take around 70 to 125 ms. As seen a full contraction of the muscle would, theoretically, produce more force than is actually necessary to play a clean note, which is on average around 0.423 kgf. The question is how fast the flexor muscles can produce just the sufficient force to play a clean note.

To answer that, let us suppose the FDP is the only force producer for the flexion of the index finger. The FDP has cross-sectional area (PSCA) of 177 mm² (Doyle et al., 2003, p.107), meaning its maximal isometric force $F0 = 177 \times 0.3N/mm^2 = 53.1N/mm^2$ (5.41 kgf). Because the FDP is a mixed composition fibre type with slightly less proportion Type I, we will consider its $V0 = 10$ lengths /s. The constants are given by: $a = F0 \times 0.25 = 13.275N/mm^2$ (1.35 kgf); and $b = V0 \times 0.25 = 2.5$ length/s. Based on that, it is possible to estimate that the FDP would need to contract just 2% of its fibre length in order to produce the 0.81 kgf required to play a clean note in virtually any position of the fretboard. In a time measuring unit, 0.2 length/s corresponds to 20 ms, the exact same time amount that Pisoni (1977) argued that listeners would need to distinguish temporal differences between two successive acoustic events, in other words, to perceive an error. Thus, in summary, an average person requires 20ms to be able to produce enough force to play a clean note on a guitar but listeners also require 20ms to perceive temporal errors. So, how is it possible to play a clean note on time? Wargo (1967) estimates that delays originating from the cognitive difficulties (disorders affecting abilities including learning, memory, perception and problem solving) ranges from 113 to 528 ms and it can only be reduced with training and anticipation of the movement. In other words, a musician needs a lot of training to master the playing technique to overcome its body's limitations. All in all, it is safe to infer that musical performance is unlikely without any type of error.

8. Guitar Performance Errors

In the field of ergonomics, performance measurements are generally associated with one of four categories: measures of speed or time, measures of accuracy or error, measures of workload or capacity demand (how difficult is to use the product), and measures of preference (Wickens & Hollands, 2000, p. 13). In biomechanics, performance is mostly characterised in terms of endurance, strength, speed, and accuracy (Sanders & McCormick, 1993, p. 215). Our research focused on measuring only the attributes that we believed would have the greatest impact on the computer models for the guitar performance. These are: precision/accuracy, speed, strength/force, and posture. Also, this paper will be limited to report only the results that that could potentially lead to some sort of performance error.

Even though biomechanical musical experiments should be very simple in both cognitive and musical terms (Heijink & Meulenbroek, 2002), which probably favours the decision to use single notes on the experiments, it has been decided to use chords (resulting from integrated movements of several digits) instead due to the fact that most finger movements made by primates (including humans) are not isolated movements of a single digit (Wing et al., 1996, p. 81).

The chord's fingering/shape was based on system known as CAGED and EDAm (Edwards, 1983). The selection of well-known chord shapes, that are movable and are usually taught on the early stage of guitar training, contributes to the extrapolation of the results to other chords with similar chord shapes. This is possible because the brain works in a similar fashion. Instead of storing all possible body positions, the brain derives new postures from a few basic ones (Wing et al., 1996).

<< Insert Fig. 4>>

Figure 4: Chord shapes used in the experiment. The 6x4 matrix objects seen in the image (also named chord diagrams) represent a guitar fretboard; the black circles inside the matrix a show the positioning for the fingers. The horizontal line linking two points represent a 'barre'. The hollow circle on top of the matrix indicates an open string and the 'x' mark indicates the string should not be played.

Three male right-handed guitarists, aged between 19 to 30 years old, took part in the experiments. All of them have had at least two years of classical training but just one actually considers himself a classical guitarist. The others sought specialization in more popular genres such as jazz, rock and blues. The subjects have between 6 and 20 years of guitar playing experience.

8.1 Force and Posture Data Measurements

The amount of pressure exerted by the guitarist's finger on the strings in order to stop them against the fretboard could impact the quality of the note produced as previously explained. To measure the isometric force exerted by the guitarist's left-hand fingers we have developed an equipment capable of recording, coping with (a) multiple hand grips (b) dynamic conditions scenarios, and (c) changes in body postures. The equipment built is dummy guitar equipped with 18 Tekscan Flexiforce sensors A201-25 (0-25lbs/11.3kgf) sensors, strategically placed, that were 'played' by the subjects while wearing a Animazoo Gypsy6 Torso motion capture exo-skeleton that records their movements. Figure 5 shows a subject trying out the setup for the experiment.

<< Insert Fig. 5>>

Figure 5 : Subject trying the force measuring apparatus. Setup composed of a Gypsy6 exo-skeleton and FoGu – a custom made guitar that records the coordinate finger's force production.

The force readings were taken by 18 sensors glued in four moveable plates that slide along the fretboard locking into pre-established positions equivalent to the inter-fret spacing of the classical guitar. The distribution of the sensors was optimised to use the fewer possible number of sensors to perform all ten chord shapes (Figure 4). The dimensions of the plates were calculated based on 9^{th} to 12^{th} fret dimensions of a guitar with the same scale length, respectively: 20.5 mm, 19.5 mm, 19 mm, and 18.5 mm. In the lower frets, an empty space was left between the plates to simulate the normal inter-fret spacing. The detail of this sensor distribution can be seen in

<< Insert Fig. 6>>

Figure 6.

<< Insert Fig. 6>>

Figure 6: Close up view of distribution sensors in FoGu.

The electrical output from the sensors was sent to an analog-to-digital converter - IRCAM Ethersense Interface - through a series of individual circuits built using 100k resistors to maximize its sensitivity. The Ethersense interface converts the analogical signal to digital and sends it to a Max/MSP patch. This patch generates an OSC (Open Sound Control) message that is captured by custom-built Max/MSP patch. The custom-built patch analyzed the input, mapped the sensors' output to the chord shapes/fingers and then recorded the force per finger. The settings used for the Ethersense interface was: Bit Resolution = 8, Sampling period = 500 ms and no average filter. To eliminate possible fluctuations caused by external factors, all sensors were recalibrated (3 measurements) before every session using weights of 102, 204, 306, 510, 0714, 1000 and 1.510 grams.

For this experiment, the subjects were required to wear the skeleton, which demands individual adjustment and the calibration to the subject's body. This means that the value recorded for a particular joint, for example wrist flexion, is relative to the flexibility of the subject for that movement (wrist flexion/extension) and a direct comparison between subjects is not possible. The purpose of using the skeleton was to understand the upper-limb configuration when performing the chords.

The subjects, wearing the skeleton, were asked to perform the same ten chord shapes used in the previous interaction with the FoGu device (see figure 5). They were instructed to apply the force they believed to be right to make the all notes of chords sound clear. The position and force should be kept for 30 seconds. This process was repeated three times to every chord shape with a 2 minutes interval between the trials. In order to avoid any effect of fatigue, the chord shape was randomized across participants.

The use of the 30 second blocks was proposed by Shan and Visentin (2003) to improve the reliability of their experiment which aimed to understand the kinematics of violin performance. Three recordings were recommend by (Mathiowetz et al., 1985) because measurements in strength studies are usually not reliable and are subject to several external inferences. The 2 minutes interval is the estimated time required to recover from the 30 seconds sub-maximal muscle contraction (up to 70% MVC).

The subjects could not rely on tactile or auditory feedback as they would normally do when performing on a normal guitar. The idea was to record the force the performers were used to apply and not the maximal force they were capable of. Any feedback could lead them to adjust the pressure, applying more or less force than normal.

The results of our force experiments have shown that, for the particular task of performing chords, the index finger is actually the strongest finger, contributing on average 32% of the force generated in a combined pinch grip. Kong and Freivalds (2003) reported that the individual fingers do not contribute equally to force production. In their experiment, they found that the middle finger is the strongest at 28.7% of the grip force, followed by the index, ring, and little fingers, with percentage contributions of 26.5, 24.6, and 20.2% respectively.

Note, however, that the resulting value has been pushed up by the barre-chords, using a different type of grip (palmar pinch grip) in which the index finger is highly stressed. The middle, ring and little finger contributed 30, 21 and 17% respectively, as seen in Figure 7.

<< Insert Fig. 7>>

Figure 7: Finger average force distribution performing the chords. The image on the left shows the average force of the fingers (y-axis) in kilogram force per subject (x-axis). The image on the right shows the percentage per finger of average force produced.

The average forces the guitarists believed was necessary to produce a clear chord is around 147 grams/f, which is 35% of the actual forced required to produce a clean note with the previously tested guitar. Obviously, that could be a significant cause of potential errors on guitar performance. Subject 2 has once again distinguished himself from the other subjects by applying double the force, on average 218 grams/f while subjects 1 and 3 have applied 120 and 105 grams/f respectively. This is the same subject that used the guide-finger as a strategy to perform the chords, a jazz guitar player. Even if the tested guitar is an acoustic jazz guitar, this professional guitar player's muscle memory indicates that only 51% of the force is required to produce a clean chord. This is something to be very aware of when modelling guitar performances.

The supposed correlation of the fret location and force production could not be verified for the non-barre chords. For the barre-chords, Subjects 1 and 3 presented significantly higher force production in the higher frets. Whatever the reason leading to this behaviour, it did not seem to affect Subject 2. Although merely speculative at this point, we are convinced that the extra-force used by Subject 1 and 3 was an attempt to overcome any difficulty originating from an awkward posture, but we were not able to check this hypothesis from the measurements made with the Gypsy6 exo-skeleton system.

Another interesting observation is that the force produced per finger on the barre-chords is lower than on the non-barre chords. In summary, barre-chords are not only slower and less-precise but also it is more likely to produce muffled and buzzed notes. Once again, it was observed a difference in the technique of Subject 2 when compared to the others; Subject 2 manages to apply less force on the lower strings to focus on the bass note. Meanwhile, Subject 1 and 3 apply more force on the lower strings. A possible explanation to this behaviour may be related to their musical background and right-hand techniques. Considering that the 6th and 5th strings (bass) are under more tension than 1st and 2nd strings, the overall technique of Subject 2 may be more efficient. If the computation considered the maximum force generated by the index finger regardless of its position in the barre, then the average accumulated force production for Subjects 1 and 3 would be considerably greater, as seen in Figure 8.

<< Insert Fig. 8>>

Figure 8: Accumulated average force. The image shows the force participation of the finger in chords per Subject, where S1 = Subject 1, S2 = Subject 2, S3 = Subject 3. The 'real force' considers the index finger maximum force in the barre as to calculate the average, whereas the normal force considers the uppermost position in the barre.

8.2 Speed and Precision Data Measurements

Music performance is a skilled activity that demands very fast and precise movements from the performer. Thompson and Dalla Bella (2006) have shown that pianists may be required to play up to 30 sequential notes per seconds over extended musical passages. Like an athlete, a 'virtuoso' instrumentalist is the result of years of exhaustive training in which his body and mind goes under continuous adaptation to maximize his genetic pre-disposition to the task. According to Wickens et al. (2004), one of the ways to improve the speed of the movements is to anticipate them, reducing the number of possible alternatives when the time to act comes . A less obvious strategy is to use body members closer to the cortex to reduce neural transmission times that could vary from 100 m/s to 25 m/s, respective to the larger and smaller (more precise) type of neurons found in the Central Nervous System.

Rosenbaum (1996) has already proven that motions can be made more rapidly in certain ways and directions because of the nature of human physical structures. This theory was formalised in a travel-cost function for the motor behaviour implies the use of basic 'stored' postures to create new ones; the selection of which 'stored' postures to use is based on the effort to move from one posture to the other. Of course, a travel function implies a departure and arrival point or posture. In our experiment, two frames of reference were proposed: one in the top (6th) and another in bottom (1st) string of the guitar (Figure 9). The use of frames of reference in different regions of the fretboard serves two purposes. Firstly, it establishes a common ground for comparison between the subjects by setting an initial posture for reference. Secondly, it will allow us to understand the influence that the initial hand position has in the overall time taken to perform the transition.

<< Insert Fig. 9>>

Figure 9: Frames of Reference developed for the experiments. The horizontal lines represent the guitar strings; the vertical lines represent the frets. The black circles with a numeral inside indicate the positioning for the fingers, where 1 = index, 2 = middle, 3 = ring, 4 = little finger.

The equipment we use to acquire the speed data was a guitar-like MIDI controller Yamaha EZ-AG that simulates the dimensions of electric guitar but, instead of strings, the controller has buttons on the fretboard. When pressed, these buttons trigger MIDI messages that are sent to the Sound Generation Unit. A bespoke real-time MIDI recorder was developed to interpret these messages and record not only the speed but also any (precision) error occurred during the experiment.

After a 5-10 minutes of warm-up, the experimenter asked the subject to set the bottom reference at the 1st frame (1st fret - 1st fret - 4th fret) and 'jump' to the first chord shape as fast and as precisely as he possibly could using a previously agreed fingering. The procedure was repeated until last frame (9th fret – 12th fret) was reached, for all 10 chord shapes, from the bottom, and top references, three times each. The chord shape recording order was: C, A, G, E, D, Am, Dm, F, B, and Bm.

Figure 10 summarize the results found. The overall speed of the chord shape was calculated as the mean of all chords for all three subjects. The same rationale was used to calculate the speed of the individual fingers. The average time for the subjects to perform a chord was around 350 ms. The D chord was the fastest at 248 ms and B chord was the slowest taking more than twice as long at 559 ms.

<< Insert Fig. 10>>

Figure 10 Average speed to perform a chord. The x-coordinates represent the time in milliseconds and the y-coordinates the chords measured.

One possible explanation for the slower performance of the B chord is the palmar pinch used in the barre technique, since it requires a different set of muscle that is stronger and slower. In addition, the B chord also requires an awkward upper-limb configuration in contrast to Am and E which are anatomically very comfortable to the subjects. Another possible explanation is related to the use of the little finger.

According to Freivalds (2004) the little finger is the slowest digit and the experiment have also showed that. It must be remembered that the overall speed of the chord is equal to the speed of the slowest link (digit) of this system. Evidence suggesting the retardant effect caused by the use of the little finger can be found when analysing the fingering used by the Subjects to perform the G-chord (on average the slowest of the non-barre-chords). While subjects 1 and 3 used the little finger in the position (1, 3), Subject 2 preferred to use the ring finger instead. Proportionally to the readings of the other chords of the same subject, the G Chord was performed much faster by Subject 2 than Subjects 1 and 3. Figure 11 shows the average speed per subject making it possible to compare and identify some patterns.

<< Insert Fig. 11>>

Figure 11: Average speed to perform a chord per subject. In the barre chart (left) the x-coordinates represent the chords and the y-coordinates the time in milliseconds. The radar chart (right) allow another comparison highlighting the patterns of speed per chord between the subjects

<< Insert Fig. 12>>

Figure 12: Average speed of the fingers when performing the proposed chords. The x-coordinates represent the finger, where 1 = index, 2= middle, 3 = ring, and 4 = little; the y-coordinates show the time in milliseconds.

Figure 12 shows the average speed per finger. As previously suspected, the little finger was indeed the slower one. Surprisingly, the ring finger has shown similar values for all the subjects, being the fastest finger for Subjects 1 and 3. As an obvious conclusion, there is a greater chance to err (time-related) when preforming chords that make use of the little finger.

Through analysis of the speed of the digits we could observe a pattern in the strategy of positioning the finger on the fretboard. While Subject 2 seems to have made constant use of the index finger as a guide, Subject 3 preferred to group his fingers before positioning them. To help us understand these strategies, the overall time to perform a chord shape was decomposed into: a) Reaction Rime (RT): the time it takes to configure and move the hand to the region where chord shape must be performed; and b) First-To-Last note time interval (FTL): the time elapsed from the moment the first and last finger was actually put into place.

The FTL is an especially important measure because it helps to reveal trends in the use of the fingers. If the FTL time is small in comparison to the overall performance time then it suggests that the fingers are being grouped and then the buttons pressed together. Conversely, if the FTL time is high in comparison to RT then one finger may have been used as a guide to set a reference to the fingers. *Figure 13* shows the RT and RTL for all 3 subjects.

<< Insert Fig. 13>>

Figure 13 : RT and FTL speeds. The percentage shown in the y-axis is related to the subject average time to perform the chord shapes. FTL = First to Last and RT – Reaction time.

The guide-finger strategy is something that the classical technique strongly recommends avoiding. Carlevaro, in 1984, already considered the use of a guide finger obsolete (Carlevaro, 1984, p. 79), but this still seems to be common practise among Jazz guitarists who adopt a less strict performance technique to match the interpretational freedom characteristic of the Jazz style. In this technique, the guide-finger searches for a note of the chord (usually the fundamental note) and only then are the rest of the fingers laid to form the chord.

For instance, Subject 2 constantly placed the index finger firstly at all the non-barre chords. In the case of the barre-chords, the middle finger was placed first. Using a radically different approach, Subject 3 has consistently positioned all the fingers on the fretboard in a very short period of time, a technique considered to be more refined. In summary, the finger's placing strategy may lead to performance error if combined to right-hand plucking/strumming techniques introducing unwanted notes or supressing important ones even if for a just noticeable period of time. It could also indicate that Subject 2 would be less prone to precision errors once, from the perspective of the motor control system, the use of a more precise digit as the guide-finger could help the performer to build an imaginary image of the fretboard in which the guide-finger sets a spatial reference for the other (less precise) digits as well as providing tactile feed-back that later can be verified by the auditory or visual senses. In order to verify that assumption, the accuracy/precision errors of the subjects were classified using a dart target-like system, as seen in Figure 14.

<< Insert Fig. 14>>

Figure 14: Error coding system. 'S' =String, 'F' = Fret, '+' = Above or Right, '-' = Bellow or Left.

In this target-like strategy of classification every error receives a code indicating the distance from the target. In the code system [S] stands for string, [F] for fret, '+' for top or right-hand side, and '-' for bottom or left-hand side. As an example, suppose that the target is the position [2, 3]. If the finger hits the positions [3, 3] and [2, 3] at the same time, this error is classified as 'S+'. If there is no hit for a particular position, then this error is classified as 'N-'. In the unlikely event of a hit outside the immediate peripheral area then a numeral is added (i.e. 'S+3'). Of course, this system is only possible if the fingering used by the performer is known beforehand. The choice of fingering was up to the subject to decided and recorded by the experimenter for later analysis.

Fitts (1954) was one of the first researchers to look into this multi-variable correlation proposing an equation which later became known as Fitt's law. According to the Fitt's law, faster movements are less accurate, whereas precise moments are slower (C. D. Wickens & Hollands, 2000, p.387). This reciprocity between time and errors has been well documented across different areas and constitute one of the fundamental tenets of ergonomics, referred to as the index of difficulty of the movement (C. D. Wickens, Gordon, Liu, & Gordon-Becker, 2004, p.263). Indeed, the data collected did reveal evidence that Fitt's law also applies to guitar performance. As can be observed in Figure 15, the fastest subject was also the least precise whilst the most precise was the slowest. Moreover, the guide-finger strategy did not prove itself very effective

<< Insert Fig. 15>>

Figure 15: Speed and Error correlation. The x-axis represents the number of errors and the y-axis the time in milliseconds

According to our results, the B chord was not only slower but it was also the most difficult to play. From the total errors 51% were generated during the performance of the B chord, followed by Bm and F chords, with 41% and 8% respectively.

It is well established that acquiring barre techniques is a difficult stage in learning to play the guitar. The strings dig into the joints and the softer parts of the index finger causing discomfort (Chapman, 1994, p.78). Discomfort, however, seems not to be the only factor that could lead to errors. The Yamaha EZ-AG guitar has buttons instead of strings and yet the errors only happened during the performance of the barre-chords (<< Insert Fig. 16>>

Figure 16).

<< Insert Fig. 16>>

Figure 16: portion of the recorded errors per type. 'S+' =hit string above the target, 'N-' = note missing, 'F-' = hit in fret left to the target, 'SF+' = hit string above and fret in the right to the target, 'S-' = hit string bellow the target.

From total recorded errors, 41% were from the 'S+' type meaning the subjects hit a string above the target. Analysing this figure further we can find that 87.5% of these errors were on the Bm and B chords, both using a barre that cover from the 1st to 5th string.

If the subject applies a barre from the 1st to 6th string but does not pluck the 6th string, this will have little impact in a produced sonority. Some performers may not even consider it an error at all. For our system however, this still counts as an 'S+' error. In reality, 78.5% of the 'S+' errors in these two chords were caused by the index finger, used in the barre technique.

<< Insert Fig. 17>>

Figure 17: Subject 2 probability error rate. The x-axis shows the percentage of the type errors type per chord.

Figure 17 shows the probability (HEP) of Subject 2 incurring an error when performing the barre-chords. Note that Subject 2 recorded the highest number of errors. Bm and B have the same statistical probability of performance errors but the repertoire of errors found in B chord is much more diverse. A profile of the error can be drawn based on its location and the finger used.

Overall, the index finger was responsible for 43% of 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 barre-chords, therefore the index finger had the highest probability of erring, having to press 5 or 6 buttons at the same time.

<< Insert Fig. 18>>

Figure 18: Fingers participation on errors. The x-axis shows the percentage of the finger's participation in the particular error types where S+' =hit string above the target, 'F-' = hit in fret left to the target, 'N-' = note missing

Although the little and ring fingers have a smaller contribution to the total of errors, they were more consistent in a particular type of error, as seen Figure 18. All the errors 'caused' by the little finger were from the 'N-' type, which one could assume is related to its lower strength if compared to the other digits. This shows that errors cannot be analysed merely by quantitative terms. In order to truthfully model precision errors, qualitative aspects of the error must also be considered.

9. Conclusion

As Sundberg (2000) observed, psychological studies of music performance have provided a wealth of information on musical expression but they have largely ignored the physical manipulation of the instrument by the performer. The interaction between humans and artefacts has been studied in disciplines such as ergonomics, biomechanics, and human factor sciences even though these studies rarely focus on music performance modelling. In reality, just a few studies actually consider the influence of the body in models for musical performance. However, it is at the physical level that accidental errors happen, known as slips. It is a well-known fact in the field of biomechanics that motions can be made more rapidly in certain ways and directions because of the nature of the human physical structures (Rosenbaum, 1996). These physical structures can limit the movement speed which would eventually induce errors.

It was demonstrated that muscle strength, speed, and endurance can indeed affect a music performance. For instance, we have shown that the index finger needs at least 20 ms to generate enough power to produce a clean note in a guitar. Curiously, this is the same amount of time that Pisoni (1977) reported for listeners to be able to distinguish temporal differences between two successive acoustic events.

The forces required to deflect a string in a real guitar were both calculated and measured; the average calculated force to produce a clean note was found to be 223 grams and the average measured force was 423 grams. If not enough force is applied to stop the string, a muffled or a buzzed note is likely to be produced instead. De facto, we have found that a buzzed-note requires on average 75% of the force necessary to produce a clean note.

Muffled and buzzed notes are especially relevant to this work because they are the direct result of the finger's inappropriate use of force. Unfortunately, these two particular 'noises' have not yet been supported by modern synthesis techniques (not even those based on physical modelling techniques). Even if currently available synthesizers were able to support noise in musical performances, there would still be the problem of controlling it; for instance, when and how they should occur. By 'noise' here we mean the result of those unintentional actions originating from motor and biomechanical forces.

In an attempt to understand unintentional actions in performance due to biomechanical constraints we have designed a set of experiments to measure not only the force produced in a multi-finger task (playing a guitar chord), but also its speed and precision. The speed results have shown that certain chords can be performed twice as fast as others, with the average speed required for a chord to be performed around 350 ms. As expected, chord shapes that better suit the hand's anatomy, such as A and E chords, presented a smaller speed variation between the subjects, respectively at 36 and 24 ms. This evidence contributes to the belief that biomechanical constraints can indeed delay some actions in music performance. The force results have shown that the average force distribution among the fingers is slightly different from what is found in the literature, where the middle finger is usually the main force producer. In our experiment, the index finger was the main contributor with 32% of force produced, followed the middle, ring and little fingers with 30, 21 and 17% respectively. The average forces the guitarists believed was necessary to produce a clean note was around 147 grams/f. The posture and motion analysis revealed surprising results. From the three articulations measured (wrist, elbow and shoulder), the elbow was the one which presented the highest level of motion, although initially it was expected that the wrist would have the higher degree of motion. These results seem interesting, but since they are very preliminary, they are not discussed in the core of this paper and must be handled with care because the equipment used was very limited to measuring just a few degrees of freedom of articulation, especially the wrist movements.

~~Although the results of the experiments have disclosed interesting evidence to support the notion that biomechanical constraints indeed interfere with music performance, we have decided not to translate these findings straight to production rules that could be used to simulate music performance. Instead, a machine learning approach was adopted as it will be discussed in future work.~~

In regard to the Ubimus, much work is still needed in order to extend the scope of current research to cope with many well-known performance issues. We are convinced that a better understanding of performance issues and models in Ubimus research (and ubimus development) is a good starting point, not only to identify the capabilities and limitations of future work, but mainly to establish a common ground for discussing several interesting questions that are still open.

Obviously, lots of experiments are necessary to obtain more evidence to support the notion that biomechanical constraints indeed interfere with music performance. Even with positive results, we think sometimes it would be not possible (or desirable) to translate preliminary findings straight to production rules that could be used to simulate music performance, but we are convinced a machine learning approach could be adopted taking such knowledge in account. Perhaps it will be investigated in our future work.

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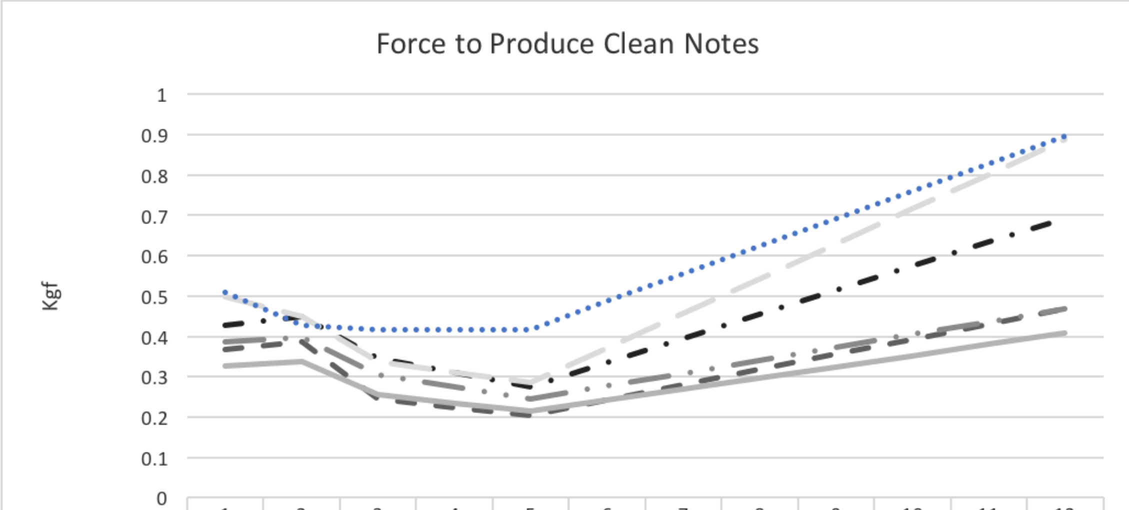

	1	2	3	4	5	6	7	8	9	10	11	12
E(1st)	0.36697	0.38736	0.24465	0.22426	0.20387	0.24174	0.2796	0.31746	0.35532	0.39318	0.43105	0.46891
B(2nd)	0.3262	0.33639	0.25484	0.23445	0.21407	0.24174	0.2694	0.29707	0.32474	0.35241	0.38008	0.40775
G(3rd)	0.38736	0.39755	0.30581	0.27523	0.24465	0.27669	0.30872	0.34076	0.3728	0.40483	0.43687	0.46891
D(4th)	0.42813	0.44852	0.34659	0.31091	0.27523	0.33494	0.39464	0.45435	0.51405	0.57376	0.63346	0.69317
A(5th)	0.49949	0.44852	0.33639	0.31091	0.28542	0.37134	0.45726	0.54318	0.6291	0.71501	0.80093	0.88685
E(6tt)	0.50968	0.42813	0.41794	0.41794	0.41794	0.48638	0.55483	0.62327	0.69171	0.76016	0.8286	0.89704

Figure 1: Measured forces to produce clean notes on a real guitar. The x-axis corresponds to the fret region and y-axis the real force (kilogram force).

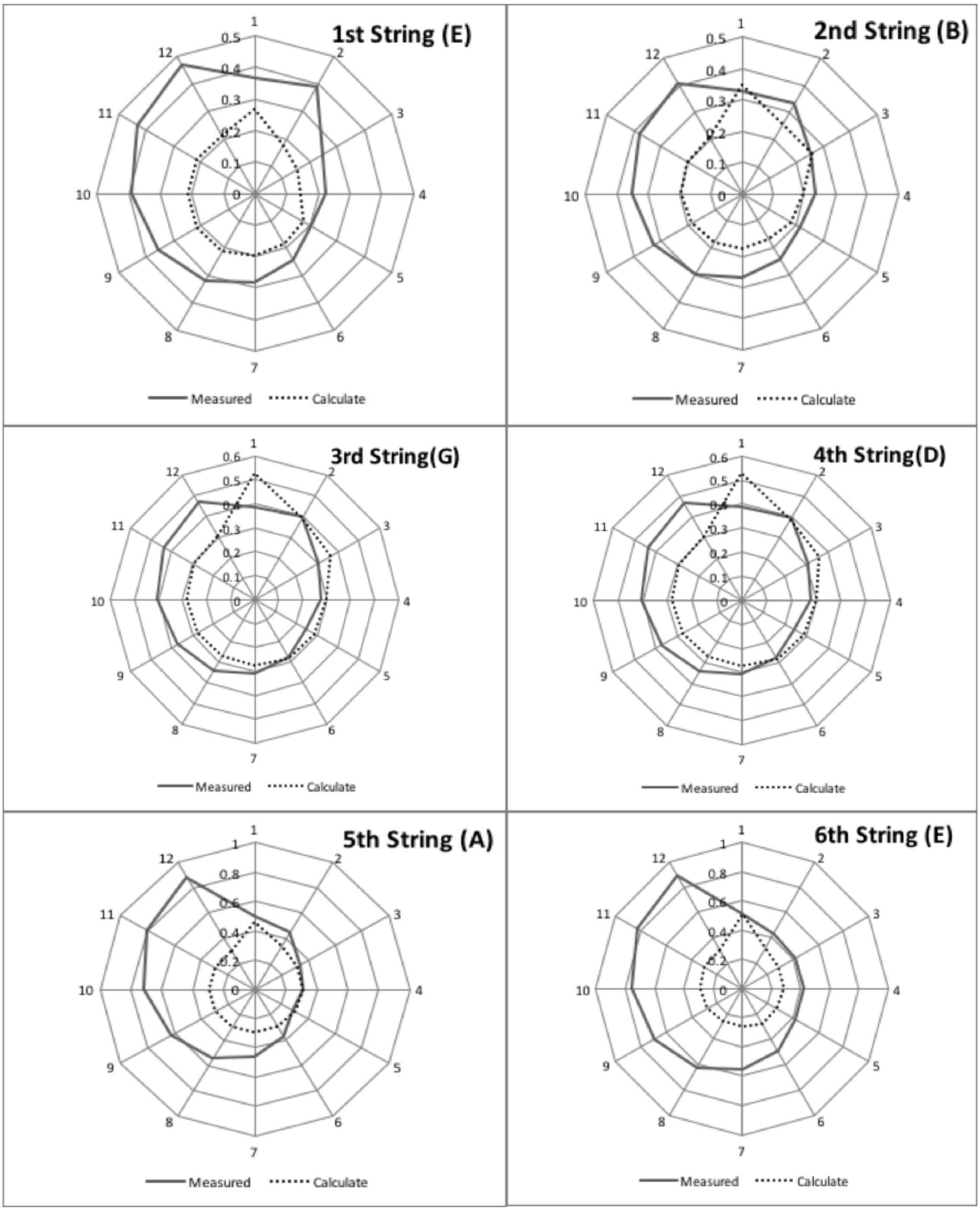

Figure 2: Calculated vs. Measured forces for string displacement. The outer circle (in blue) shows the measured force and the inner circle (in red) shows the calculated force. The fret regions are shown in the peripheral area of the chart.

Figure 3: F (Barre) Chord Shape

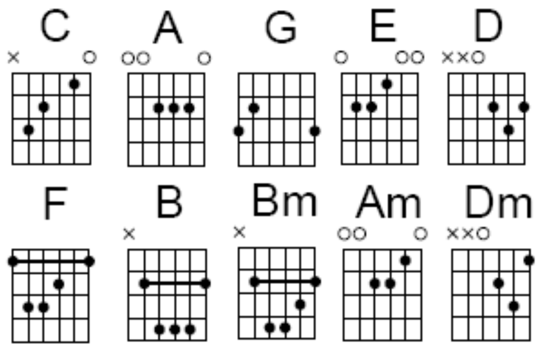

Figure 4: Chord shapes used in the experiment. The 6x4 matrix objects seen in the image represent a guitar fretboard; the black circles inside the matrix a show the positioning for the fingers. The horizontal line linking two points represent a 'barre'. The hollow circle on top of the matrix indicates an open string and the 'x' mark indicates the string should not be played.

Figure 5 : Subject trying the force measuring apparatus. Setup composed of a Gypsy6 exo-skeleton and FoGu – a custom made guitar that records the coordinate finger's force production.

Figure 6: Close up view of distribution sensors in FoGu.

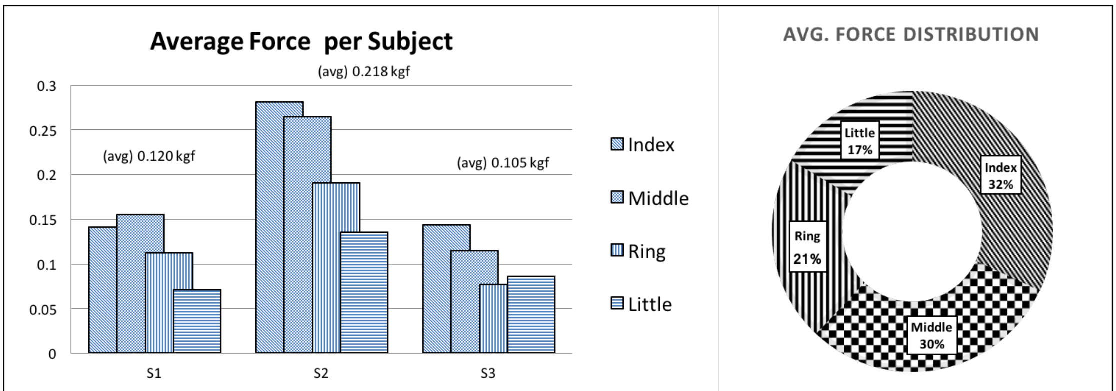

Figure 7: Finger average force distribution performing the chords. The image on the left shows the average force of the fingers (y-axis) in kilogram force per subject (x-axis). The image on the right shows the percentage per finger of average force produced.

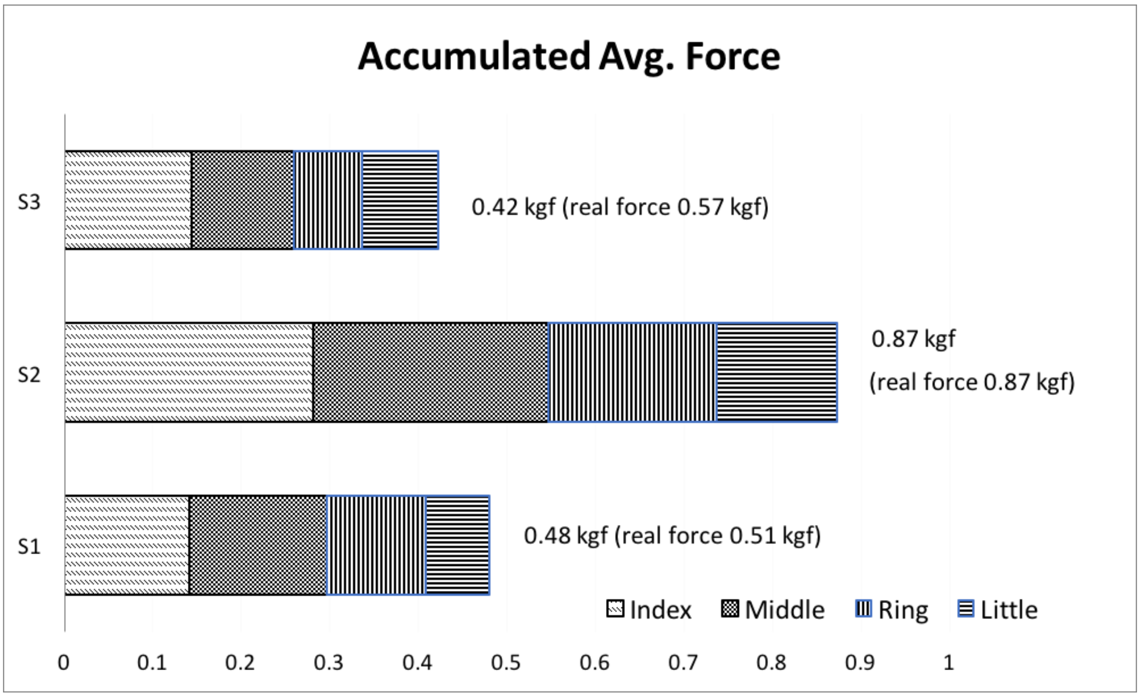

Figure 8: Accumulated average force. The image shows the force participation of the finger in chords per Subject, where S1 = Subject 1, S2 = Subject 2, S3 = Subject 3. The 'real force' considers the index finger maximum force in the barre as to calculate the average, whereas the normal force considers the uppermost position in the barre.

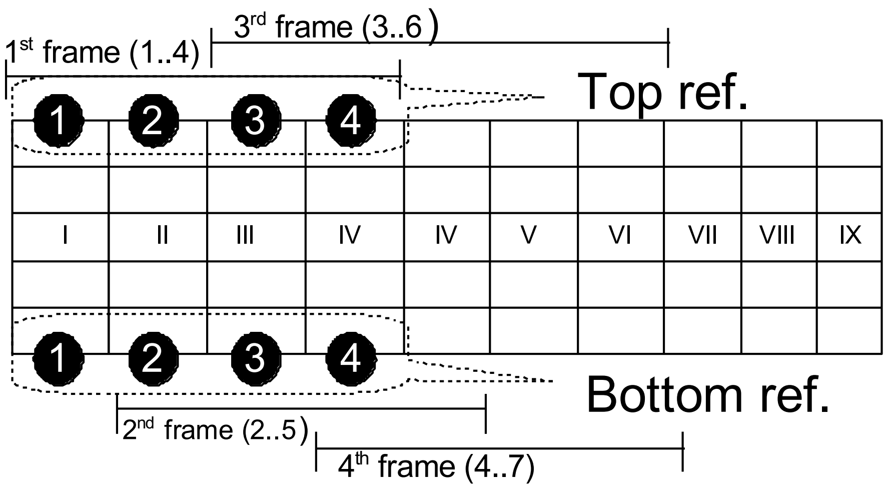

Figure 9: Frames of Reference proposed for the experiments. The horizontal lines represent the guitar strings; the vertical lines represent the frets. The black circles with a

numeral inside indicate the positioning for the fingers, where 1 = index, 2 = middle, 3 = ring, 4 = little finger.

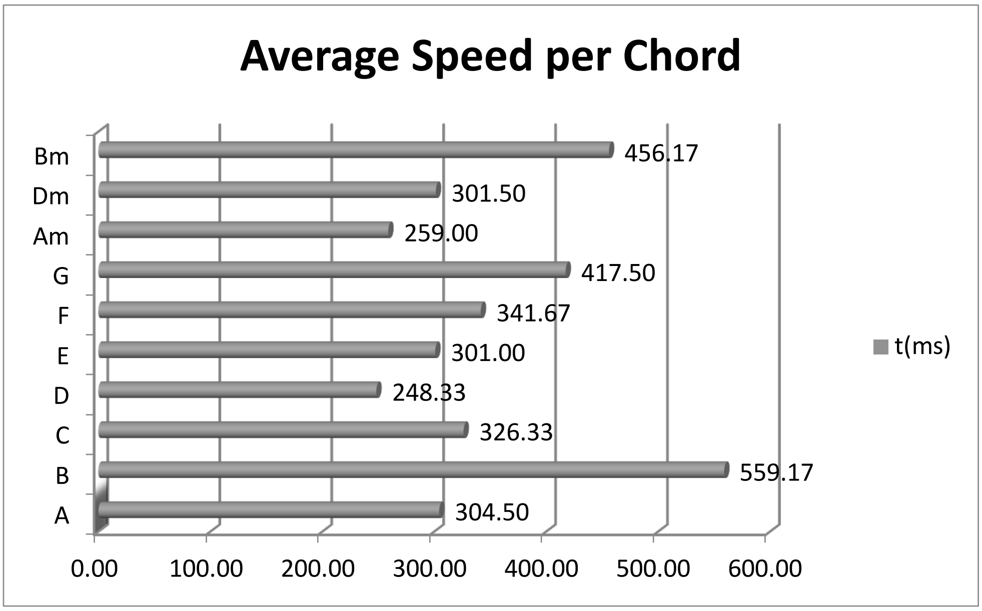

Figure 10 Average speed to perform a chord. The x-coordinates represent the time in milliseconds and the y-coordinates the chords measured.

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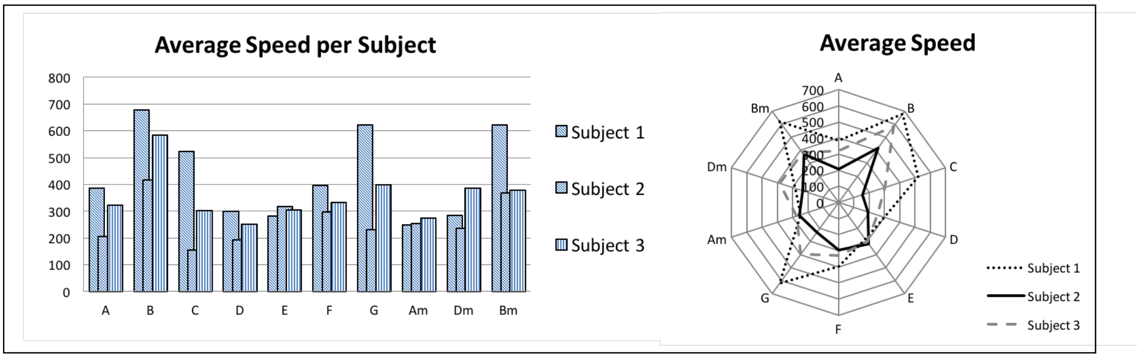


Figure 11: Average speed to perform a chord per subject. In the barre chart (left) the x-coordinates represent the chords and the y-coordinates the time in milliseconds. The radar chart (right) allow another comparison highlighting the patterns of speed per chord between the subjects

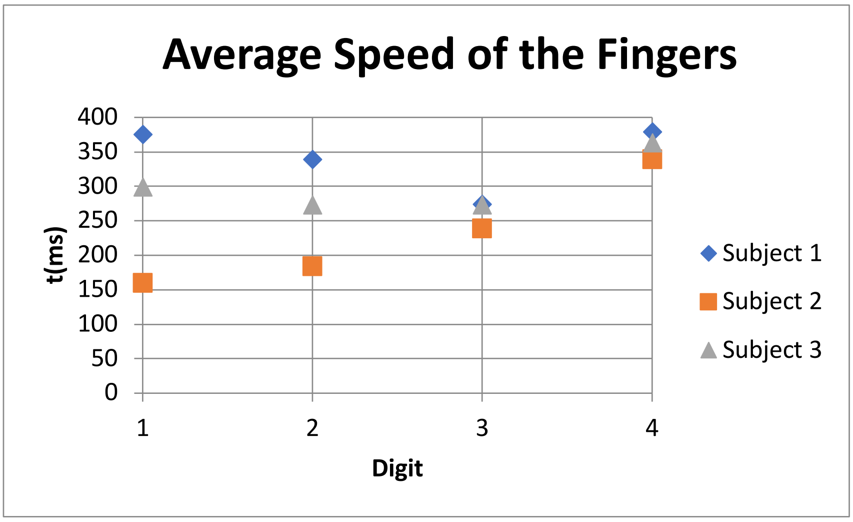


Figure 12: Average speed of the fingers when performing the proposed chords. The x-coordinates represent the finger, where 1 = index, 2= middle, 3 = ring, and 4 = little; the y-coordinates show the time in milliseconds.

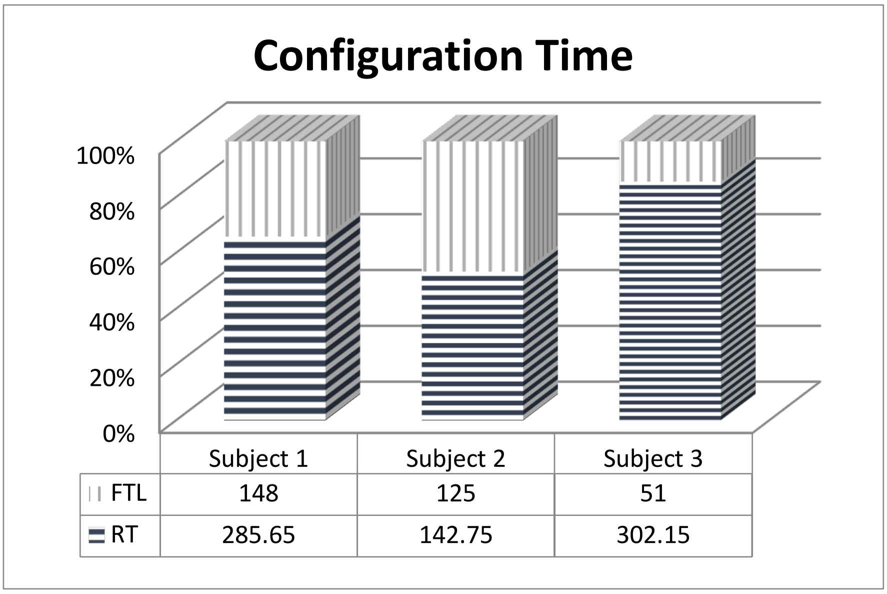


Figure 13 : RT and FTL speeds. The percentage shown in the y-axis is related to the subject average time to perform the chord shapes. FTL = First to Last and RT – Reaction time.

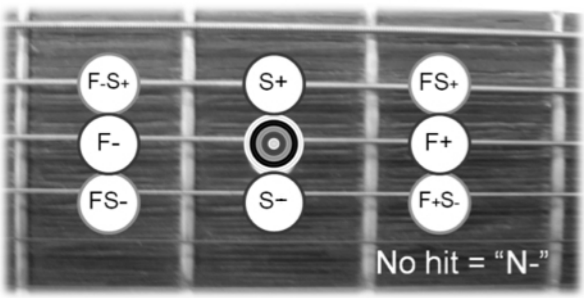


Figure 14: Error coding system. ‘S’ =String, ‘F’ = Fret, ‘+’ = Above or Right, '-' = Bellow or Left.

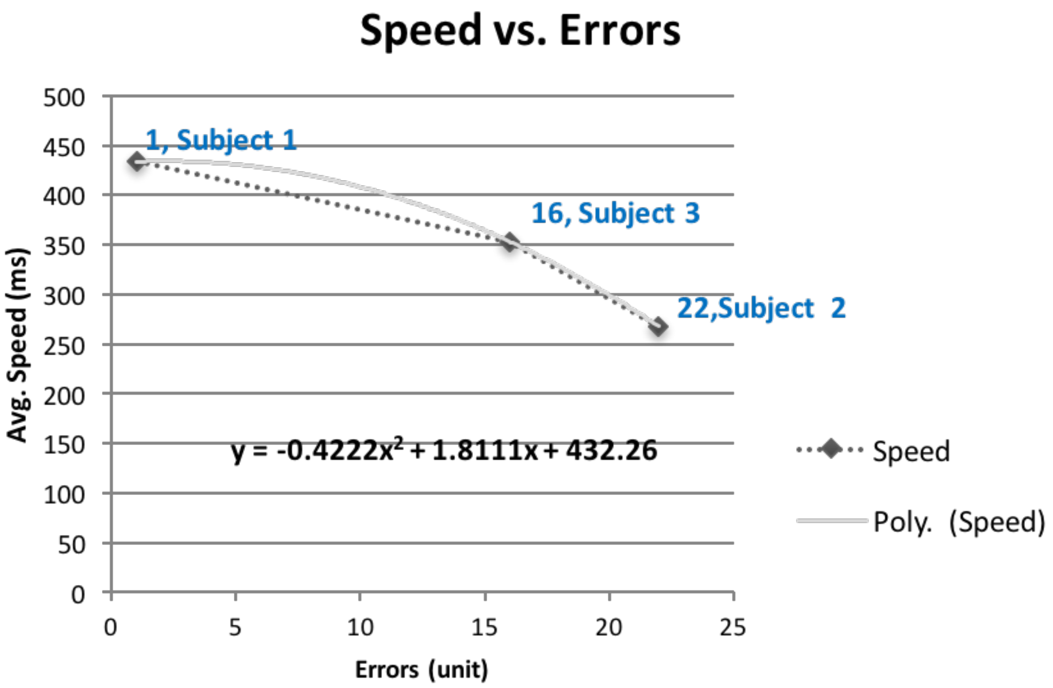


Figure 15: Speed and Error correlation.The x-axis represents the number of errors and the y-axis the time in milliseconds

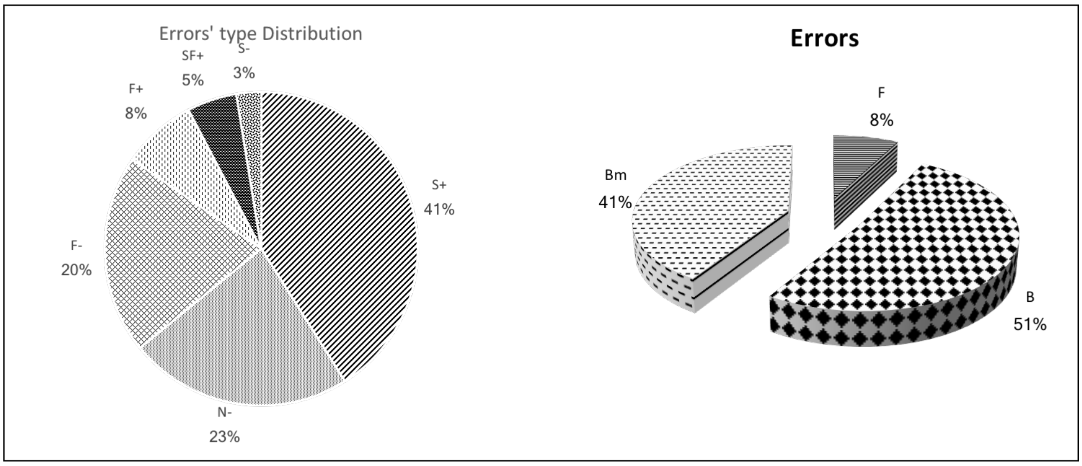
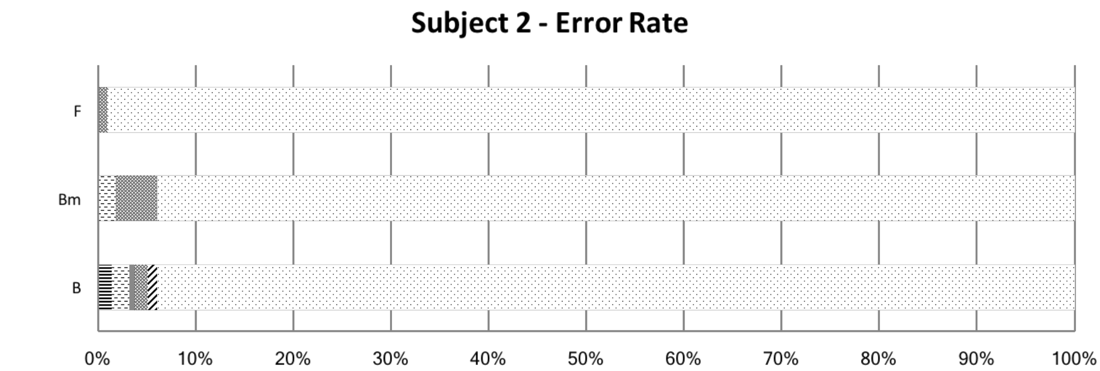


Figure 16: portion of the recorded errors per type. 'S+' =hit string above the target, 'N-' = note missing, 'F-' = hit in fret left to the target, 'SF+' = hit string above and fret in the right to the target, 'S-' = hit string bellow the target.



	B	Bm	F
F-	0.013888889	0	0
F+	0.018518519	0.018518519	
N-	0.00462963	0	0
S+	0.013888889	0.041666667	0.009259259
SF+	0.009259259	0	0
Total hits	0.939814815	0.939814815	0.990740741

Figure 17: Subject 2 probability error rate. The x-axis shows the percentage of the type errors type per chord.

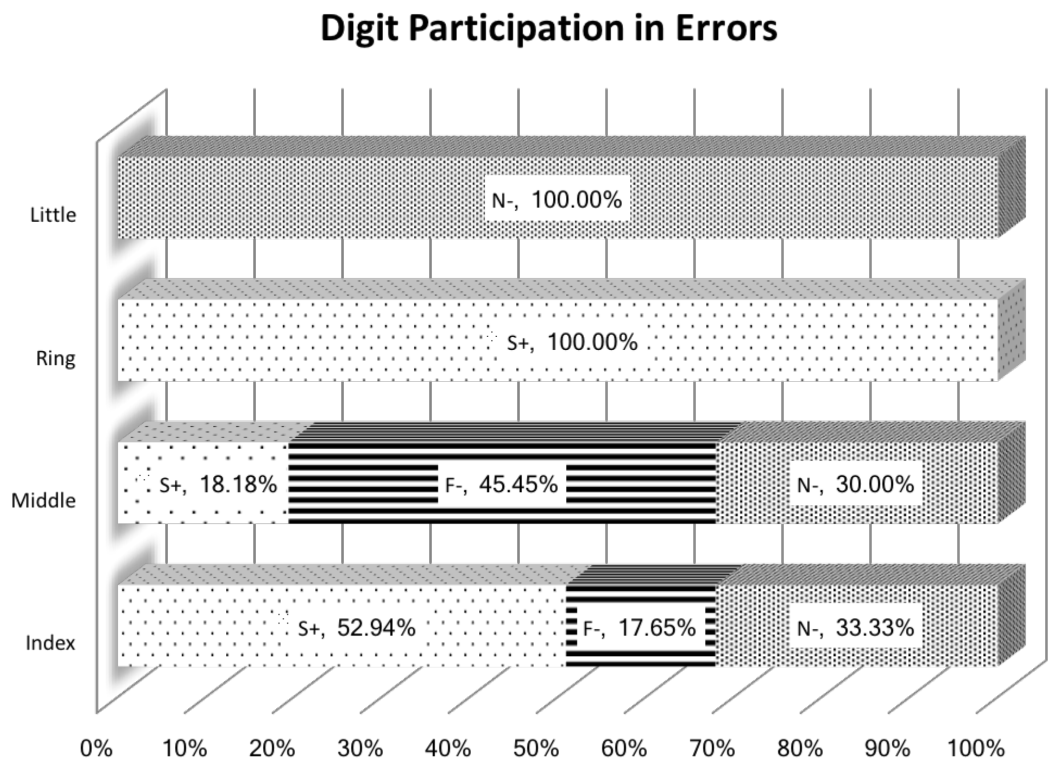


Figure 18: Fingers participation on errors. The x-axis shows the percentage of the finger's participation in the particular error types where S+' =hit string above the target, 'N-' = note missing, 'F-' = hit in fret left to the target