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Towards Modeling Guitar Chord Fretboard Finger Positioning using Electromyography

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ABSTRACT

We explore the use of forearm electromyography (EMG) as a gestural input interface, or the captured biofeedback signals found in the muscles, towards modeling how beginner and seasoned guitar users plot chords in the fretboard. We intend to contribute to a paradigm of studies that propose a new set of interactions with an existing device, integrating machine learning techniques. Data was collected from ten(10) participants using the Myo™muscle armband. Data on the forearm EMG signals when fingers fret the chords A to F were recorded, preprocessed and transformed into a balanced and normalized dataset that was later on fed into a machine learning task in order to build a model. The model performs with an accuracy of at least 79% with 0.8 kappa statistic following a Bayesian classifier. Such model is expected to be used to train the computer and early learners of the guitar possibly with the goal of creating a synthesizer without any more requiring a MIDI interface or an actual guitar. This can be pushed further towards building an air guitar model.

CCS Concepts

•Human-centered computing → Gestural input;

Keywords

Electromyography, machine learning, user modeling, guitar chord, fretboard

1. INTRODUCTION

We follow the standard guide towards positioning the finger in the guitar fretboard as defined by [14]. Thru this, we aim to explore opportunities to provide avenues for creative expression using natural human gestures eliminating the need for visual input. Such visual inputs are usually disrupted when blocked in vision or when lighting does not play in the way of the gesture source. Since most visual input-based gestures read by the computer are also seen with major lags and delays in processing, the entire experience can pose to be difficult or sometimes even frustrating.

In this paper we address the possibility of offering the same gesture experience but with lesser delays exploiting the actual source of gestures - the muscles themselves, specifically forearm electromyography. We aim to build a model that will train the computer to detect gestures based from biophysiological signals read from a human user while wearing a specialized muscle armband. Exploiting the *Air Guitar* concept, our proposed interaction eliminates the need for any other specialized hardware/interface that might pose certain hygiene-related or even musculatory constraints (such as maintaining cleanliness of fretboards, callousces from over usage of fingers, avoiding instrument damage due to possible sweat or developing musculatory related diseases such as Carpal Tunnel).

This paper aims to build a general model based from inputs of actual guitar users while they fret a chord in the said instrument. This way, a computer can be trained to understand muscle data when a user "poses" executing the intended chord. Furthermore, the proposed interaction will provide opportunities for enthusiast learners and musicians to learn how to play the guitar with the help of a synthesizer.

There are numerous possible applications for this proposed input which will be discussed in the Future Work section of this paper. The details in data collection, methodology and model results, even related work are discussed as well in the succeeding sections of this paper.

2. RELATED WORK

Development and research in Computer Human Interaction thru the decades have focused more on providing brand new interfaces - probably thru the use of touchscreens [20], stylus pointers [10] to name a few. Similarly these innovations have focused on the device rather than the experience by the users. In the realm of games, joysticks have evolved in many forms [4]. All these have allowed the users to sit comfortably and require the use of both hands or a surface. Other interactions have decided to focus on the actual movement of the users to possibly reduce cases of obesity and promote other healthy activities such as weight management[18]. While all these works exhibited impressive results in their domains, the growth of technology has grown pervasive towards further improving the experiences of the user. The main focus of this research is to contribute to the array of solutions that does not require an unobstructed vision therefore fostering a stimulated and active movement

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that is also natural, seamless and interactive.

Perhaps the most popular work that resembles the Air Guitar is the work by [1] which has been inspired by the original work done by [2]. Not until then, only a limited set of studies have decided to focus on such proposed interactions. These studies have displayed significant achievements and impressive results however validation will have yet to be improved and measured realistically through user-centric approaches rather than through techniques that required traditional software engineering principles. The work of [9] has been successful in creating an actual air guitar with a musical synthesizer. Said study employed magnetic tracking, accelerometer data along with computer vision to model the gestures. It also tackled the several delays and lags from the recognition to the musical synthesis. Yet it was not able to totally improve the experience since the inputs, though gestural are dependent on what the computer can see rather than the actual moves exerted by the user. This poses a challenge on how real are the gestures and do they really match with the ones executed by the user and the ones read and understood by the computer.

There are even more limited works on integrating music and interactions[3] but the most recent and saturated works are in musical conducting and its gestures [12, 6, 8]. In the work of [5] musical features were used and fed into a similar machine learning task to identify features that describe the genre of the music. The Myo was first popularized in the work found in [15] and has been used in several applications such as hand navigation[13], teleoperation[19], and even musical interaction [16].

In the latter goals of this research, a musical synthesis can be done to possibly link the features in the music of an actual guitar chord *vis-a-vis* to the features in the muscle movement as recorded from the forearm. Several works on music, interaction design and machine learning will be integrated towards the modeling of the data used in this study as a continuation and improvement from the work of [7].

3. METHODOLOGY AND FRAMEWORK

Considering early work, this paper includes only the first part of a bigger research study. Research methodology included (1)Data Collection and Preparation and (2) Model Building. It is important to note that only the first part of this study is included. The latter part is still to be commenced. These parts include prototype building or a tool that reads from the model; testing and validation following user experience metrics. The included scope is described by Fig 1.

3.1 Data Collection and Preparation

A sample of ten(10) guitar enthusiasts took part as respondents in the data collection of this study. Their average years of experience in playing the guitar is 5.3years. The level of expertise varies from beginner, intermediate, all the way to the casual professional. All participants were regular guitar players. A regular guitar player is defined as an individual who strums with his right hand and frets the chords with his left hand. Each participant was equipped with the Myo Armband Muscle sensor placed on their left forearm which recorded the electromyography data whenever a chord is played on the fretboard. The standard octave of 7 chords namely C, D, E, F, G, A, B were played by each participant. Each participant struck the chord on the fretboard. These were recorded while they were wearing the Myo armband sensor. A total of 5 repetitions were asked from each participant for each chord forming a data set matrix composed of 7x5x10 entries. The raw EMG data along with their accelerometer and gyroscope data were recorded and included. Also, the correlation of each data source and channel were added into the data set.

			Feature Data	
Feature	*min*	*max*	*mean*	*stddev*
EMG1	0.00	0.41	0.23	0.05
EMG2	0.00	1.00	0.64	0.06
EMG3	0.00	1.00	0.59	0.08
EMG4	0.00	1.00	0.49	0.12
EMG5	0.12	1.00	0.36	0.09
EMG6	0.00	0.53	0.35	0.04
EMG7	0.00	0.77	0.47	0.07
EMG8	0.03	0.66	0.29	0.07

Table 1: Statistics on the EMG Channel Data

features
EMG Channel 1
EMG Channel 2
EMG Channel 3
EMG Channel 4
EMG Channel 5
EMG Channel 6
EMG Channel 7
EMG Channel 8

Table 2: EMG features selected

Referring to the Myo armband sensor described in Fig. 3, the center-most channel with the Myo logo represents channel 4. Channels 3 to 1 are from the center going to its left. Channels 5 all the way to 1 are from the center going to the right. The Myo armband is worn with the logo facing away the user and the channel 1 directly below a person's elbow. It is important to note that the armband should be worn on the widest part of the forearm. Refer to the proper way of wearing the Myo as shown in Fig 4.

After careful analysis and preprocessing, each chord were labeled with the appropriate chord class. To eliminate extreme values and outliers, the interquartile range approach was employed. To review, the interquartile range formula *IQR* is defined in the given equation.

$$IQR = Q_3 - Q_1 \qquad (1)$$

The *IQR* value eliminates values that are found at the extremes of the range of values. This is applied to eliminate outliers and extremeties [17] as an alternative to mean, median and standard deviation. Apart from this, the data set was further normalized and a final set of features were selected and identified before it is fed into a machine learning classifier towards a modeling task. The $InfoGain$ attribute evaluator along with the *Ranker* search technique was used to select and rank the features that would be most useful for the dataset. The identified features are seen in table 2. The Myo armband is equipped with 11 channels all in all but only the 8 channels which are placed on top of the cartilages and muscles found in the forearm, that control movement of the fingers were deemed to be useful and relevant in this modeling task. Apart from this, the standard deviation and the average values of each EMG channel in relation to the other channels were found to be relevant. This somehow establishes the correlation of each channel with one another. The

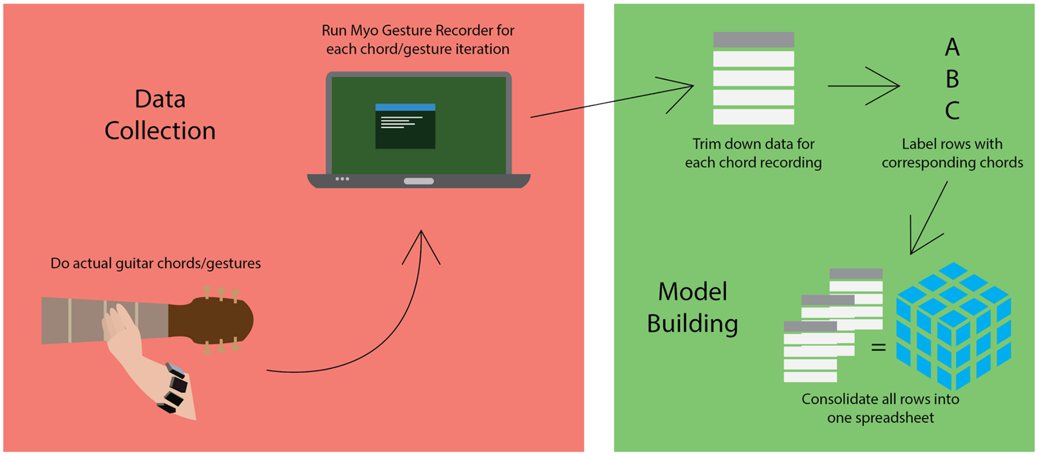

Figure 1: Framework of the methodology employed in this study

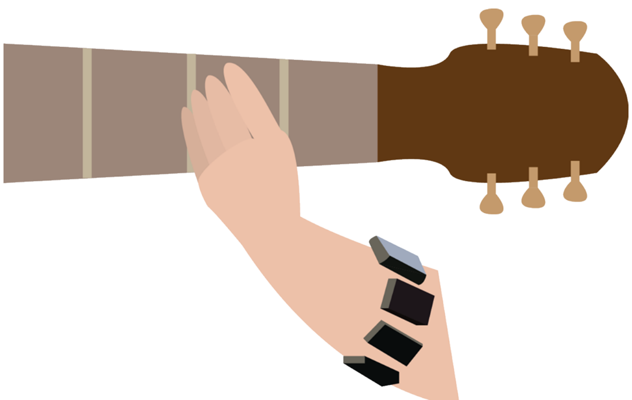

Figure 2: Demonstration of the positioning of the myo placed on the muscle forearm during recording of the chords. Image generated by team.

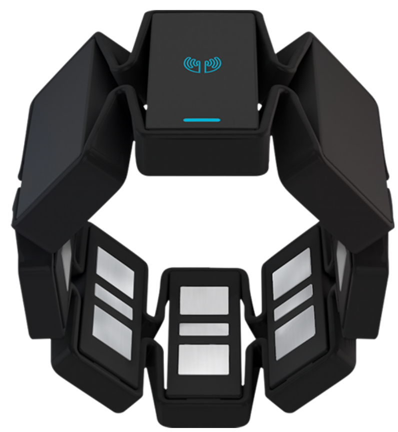

Figure 3: Myo armband developed by Thalmic Labs. Photo for display purposes only.

last item enumerated corresponds to the label used in identifying each of the instances in the data set.

3.2 Data Modeling

The preprocessed dataset was fed into a machine learning task in order to build a model. Several machine learning algorithms were employed to measure if the model exists and does not fall under accuracy paradox. Specifically, Bayesian, Decision Tree, Connectionist (multilayer perceptron) and lazy (Instance-Based) classifiers were used but only the Bayesian classifiers will be used to build the model. In focus, a simple Naive Bayes classifier as described by equation 2 was utilized, a multilayer perceptron where the former describes a hyperbolic tangent while the latter describes a logistic function ranging from 0 to 1, which is similar in shape. as described in equation 3 and 4.

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)} \tag{2}$$

Figure 4: As demonstrated the proper way and positioning of the Myo armband if worn on the left forearm

		Model Results	
Classifier	*Accuracy*	*Kappa*	*MAE*
Naive-Bayes	79.8%	0.76	0.05
Multilayer Perceptron	91.5%	0.90	0.03
J48	82.9%	0.80	0.04
KNN*	89.0%	0.87	0.08

Table 3: Performance Measures on the Model

where the p or the probability values describe the conditional independence of the class C from the features following a certain law on probability [11].

$$\gamma(v_i) = tanh(v_i) \tag{3}$$

$$\gamma(v_i) = (1+e^{-v_i})^{-1} \tag{4}$$

All machine learning classifiers were employed with the use of the RapidMiner tool. The standard inputs and parameters such as hidden layers, learning rates were employed. For all classifiers, a 10-fold cross validation technique was used. The accuracy results, mean absolute error and Kappa Statistic were used as basis on measuring the performance of the model. In this study, the performance of each of the model was used as a benchmark in order for results to be carefully analyzed. A more realistic data set is preferred rather than a high performing model which is not as realistic as expected. From the given list of machine learning classifiers, the classifier with the lowest performance will be put in to consideration. This is because while the feature selection criteria establishes correlation between the features, it is ideal to find whether these attributes can significantly affect the model independently.

4. RESULTS

The classifier where the model performed the best was the MultiLayer Perceptron having performed at 91.5% and kappa statistic value of 0.90 which describes an *almost perfect agreement*. The instance-based classifier KNN performed second to the best in terms of accuracy and kappa statistic. It is important to note that for K, the standard value between labels and classes as described by the equation below has been used to be able to derive the right value for K.

$$K = \frac{N_c + N_f}{2} \tag{5}$$

Though the Naive-Bayes classifier is most used towards analyzing related EMG data, it has performed lowest among the four classifiers. This can give us an impression that the other three classifiers provided a common ground when it comes to the strong features of the data set.

In order to analyze the weaknesses in the model thru data set, we can use the confusion matrix from the Naive-Bayes classifier. This can give us an analysis on the gestures per chord where the machine was mostly confused with.

							Naive Bayes
a	*b*	*c*	*d*	*e*	*f*	*g*	*classified as*
38	3	0	3	0	7	0	a = d
0	44	1	0	0	0	6	b = e
0	0	45	0	0	0	6	c = f
2	0	0	47	0	2	0	d = a
0	0	0	0	51	0	0	e = b
15	0	0	8	0	27	1	f = c
0	9	8	0	0	1	33	g = g

Table 4: Confusion Matrix for the classification done with Naive-Bayes Machine Learning Algorithm

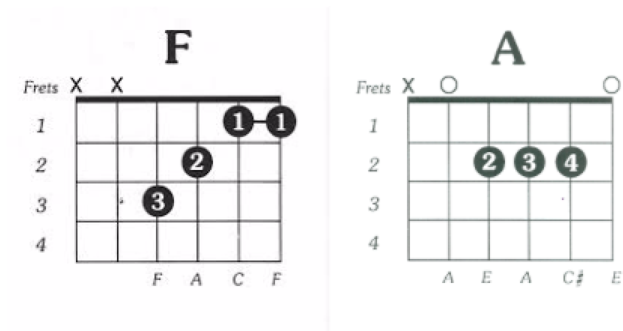

Figure 5: Acoustic Guitar Form of Chord A

Looking closely on the confusion matrix found in Table 3 we can see the performance of each chord in contrast with the other chords. It is important to note here that we are analyzing the muscle movement in the forearms when striking the chord on the guitar fretboard. We can see that 15 instances under chord A, which should have been classified as A, has been incorrectly-classified as chord F. It can be assumed that the guitar chord F is sometimes confused as guitar chord A. See acoustic guitar form for Chords F and A. It is observed that though chords F and A do not look entirely alike, there are similar features found. The chord A is executed in the fret by positioning fingers in positions 3 and 4 (see Fig. 5) and these two positions are adjacent to each other.

Similarly, Chord F is executed in the fret by positioning fingers in positions 1-1 (see diagram) and these two positions are adjacent as well. While the height of these positions on both chords are noticeably different, the muscles and their movement involved are somehow similar. These will have yet to be investigated on a deeper approach. Similar confusions will have to be fine tuned with further data. The other chords displayed a more neutral relationship citing lesser confusions comparable to that between chords F and A.

5. CONCLUSION AND FUTURE WORK

The study was able to build a data set which consisted of processed EMG data and features from seven chords namely C, D, E, F, G, A, B. Though understanding the intricacies of musical composition and the complexity of music as a paradigm, there is a need to expand into other types of chords like the major and minor chords (Gsus, Am7 to name a few). This way we can come up with a wider data set which can be more accurate or realistic.

The data set's accuracy performed at the 79% in its lowest which is still subject to several improvements especially if the data set will have a greater number of instances per chord. The achieved accuracy is above average but can still be improved by doing some further processing. In the long run the study shall push towards real time recording of chords so that that we can synthesize a more realistic model and a more seamless interaction. For now, the existing model works towards a learner-focused fretting of the chords where the user is expected to be on a beginner level. For more advanced users and professional guitarists, a more accurate model with a realistic modeling approach would be more appropriate. There is now a need to create a prototype where the model can be potentially applied so that it can now produce and synthesize the sound of the chord that has been detected from a certain user doing the air guitar pose.

The study is also looking towards synthesizing and modeling the different types of strums and plucks so that these can be integrated into a prototype that can be used to actually synthesize music at an advanced level. The communication and lag between two sources would need to be investigated as this was not fully addressed in this stage of the study.

Using the recommendations from existing studies, the EMG work can be integrated with EEG data to possibly find a correlation between the electromagnetic energies emitted from the brain and the muscle forearms. Towards a more computationally-creative implementation of machine learning, there will soon be a need to handle data using time-series applications which would be more appropriate for series of data and their features, that contain a time-dependent attribute. More importantly, the produced model from the said number of participants can be used as early groundwork for the succeeding studies and future work envisioned in this study.

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