Building Guitar Strum Models for an Interactive Air Guitar Prototype

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ABSTRACT
In this work-in-progress, we propose the design of an interaction that allows a guitar player to air guitar with the use of forearm Electromyogram (EMG). We integrate results from our previous study where we have used the same medium in training a classifier to recognize standard guitar chords. In this paper, we aim to train a classifier this time to recognize the different types of strums when playing the guitar. We collected data from ten (10) participants using the Myo armband doing strum repetitions for at least fifty (50) times. The strumming EMG data was then pre-processed and fed into a machine learning task to build a model. A k-Nearest Neighbor (*k=11*) classifier was trained and yielded an accuracy of at least 46% accuracy with a kappa statistic of 0.3712. Model results describe that data size needs to be improved while considering equally the same set of features. Additionally, user insights and feedback on the armband usage as an alternative creative medium was gathered from our target respondents. Different views and insights are stated which opened opportunities for the improvement of the actual air guitar concept as a creativity tool.

ACM Classification Keywords
H.5.J.5 Information Interfaces and Presentation: Sound and Music Computing Modeling

Author Keywords
EMG; Interaction Design; User Modeling; Air Guitar

INTRODUCTION
The acoustic guitar is one of the most fascinating and most used musical instrument popular to most types of musicians, be it a novice or a veteran performer. There are standards and approaches in the positioning, handling, fretting of chords and strumming and plucking with regards to using the acoustic guitar. Most of the time, the novice learner adjusts to the grip, texture and overall structure of the said musical instrument. Over long periods of time, an experienced guitarist acquires the skill to perform and play the musical instrument with ease and grace. In this creative process, composer musicians accompany themselves with a musical instrument when trying to compose lyrics and chords to produce a musical piece. The typical approach involves a composer sitting on his seat, with pen and paper and his guitar simultaneously writes down as he composes his musical masterpiece (see Fig 2). In this setting, the hands of the composer musician switches between strumming the guitar strings, fretting the chords, to actually taking down notes in his musical sheet. In the case of a mobile tool such as Finale, the pen and musical sheets are replaced with either the fingers or stylus and the mobile tablet. In both approaches, the composer musician is taking hold of the guitar and switches grips as he changes the current task. We believe that this approach might be too problematic and might disrupt creative momentum while composing. In this study, we design an interaction that can remove the physical guitar during the composition process, towards hopefully enabling the musician composer to *air guitar*. Specifically, we intend to discover if it is possible to design and train a classifier of strums in order for us to develop an integrated prototype combining the said classifier and the guitar chord fret classifier. In the long run we envision musicians to be able to augment their composition process when an idea comes into mind without having the need to actually pick up the guitar. Thru this, they would be able to play back just by strumming in the air without any thought disruptions or losing a note that comes into mind. In this paper we discuss previous work on the guitar fretboard and integrate model results on training a computer model to identify different types of strumming. A certain strum is defined by using the wrist to brush the string either upwards or downwards using your finger/nail [13]. Details on the data collection, study design and protocol and model building are described in the latter section. We were also able

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to acquire user insights and feedbacks regarding the proposed architecture as seen and described in Fig 1. In this work-in-progress we shall discuss the features, results of Phase 2 in the roadmap. As seen in the project roadmap in Fig 1 with phases 1 to 3, we continue the work of [4] from phase 1, proceeding to phase 2. In this phase, we intend to build a model and classify whether the user strummed downwards or upwards. See Figure 1. We will also discuss the data collection process, how the model was built. We have also included a brief discussion of the analysis and results of the findings on the guitar fretboard as compared to the strums we have collected in this study. In the succeeding sections we shall also discuss our findings and the next steps needed to complete the study.

RELATED WORK

We believe that musical interaction is an important and fascinating approach that allows players and performers to work in freestyle with the actual instrument. We have found many studies and attempts to bridge and use technologies in line with working with musical instruments such as helping and motivating performers [14], introducing new techniques on how to learn to play the guitar by the use of hand tracking [12], using augmented reality with auditory responses while guitar learning [9] and many others. We have also found some studies that have been user-centric and have integrated newer techniques. The study of [9, 7] enable the use of computers and tracks the actual hand gestures made by the guitarists when they perform. We believe that these studies create a new approach in guitar playing but there have been issues in performance such as lag, mobility, safety and even motion sickness [9]. We believe this is where the Myo armband could play a role in addressing the issues encountered in trying to design seamless interactions with musical instruments. In the studies of [11, 4], we were able to discover that the usage of the Myo can be made effective in obtaining motion and muscle sensing with reported accuracies as much as 79%. We believe this demonstrates potential as a gestural input device that can recognize patterns and can be then used as an alternative medium to the guitar learner and composer. We believe that interaction with music is a cross-cultural tool for collaboration and communication [6, 10].

METHODS

Participants

We recruited ten (10) participants using snowball sampling technique by posting on social media the scheduled date for the data collection of the project. Participants' gathered, were aged from nineteen (19) to twenty-four (24) and mostly, consist of students. The average years of experience of the guitarists is seven (7), ranged from two (2) to fifteen (15) years of total individual experience. A certain guitarist is considered as a newbie, if the guitarist has less than seven (7) years of experience and does not have constant practice for two (2) weeks. All of the participants of the study are male and right-handed. Each participant has their own unique strumming style and technique which results to a variation in finger and guitar position. All of them was provided with a Myo armband, to record their muscle movements in a downward and upward motion. See Figure 2. An initial project briefing is then conducted to start with the data collection.

Study Design and Protocol

In preparation to the data collection, one week schedule was made from Monday to Thursday, completing the ten (10) participants, with at least two (2) participants per day. The location was set in a private closed room with an open space and a calm surrounding. Each participant is reminded through text messages prior to their scheduled data collection. A thorough briefing is then conducted before performing the upward and downward strums and the participants were at rest until further notice. Before collecting the data a classical guitar with six (6) steel strings is prepared by the group and was used by all the participants. Each participant was given an informed consent form which contains the study procedures and the objectives of the project. Once the participant has already reviewed the document, the participant will then sign the paper and proceed to the data gathering proper. Each participant was then assisted by the group in having their custom calibration of the Myo armband prior to data collection. The Myo armband is specifically placed between the *Ulna* and *Cubital fossa* under the extensor superficial layer portion of the forearm [5]. All of the participants are instructed to sit down on a stacking chair in the position seen in Figure 2. With at least five (5) trial sessions of performing both up and down strums, a timer is then prepared before the start of the actual recording. The actual time is recorded as the participants received instructions to perform a total of fifty (50) repetitions in both upward and downward strumming motion. With an estimated time of about twenty (20) to thirty (30) minutes per participant, the average time of all the participants is 26.3 minutes. After each session, the data collected was then stored and classified based from date, name and to whether the data is an upward or downward motion. We have also prepared a pre-structured survey and conducted a short interview afterwards. We sought for their insights with regards to the Myo as a consumer device and as an alternative for the actual guitar. We prepared the survey to have ten (10) closed ended questions in a four (4) point Likert scale format. The results are then converted to their percentage format which then be classified and analyzed based from the degree of answer to a certain question. See Table 1. To get deeper insights on the actual air guitar project, we verified the result through an interview with four (4) more questions prepared:

- IQ1 - What are your positive and negative feedback about the air guitar project?
- IQ2 - What are your thoughts about the Myo armband as a tool for learning how to play the guitar?
- IQ3 - Do you believe that the Myo armband can be an entire replacement of an actual guitar?
- IQ4 - Do you prefer to purchase a Myo armband with the same price as an actual guitar?

Each given feedback by the participants were written down in their own data folder, alongside with their strumming data. With the survey itself, and through the conducted interview,

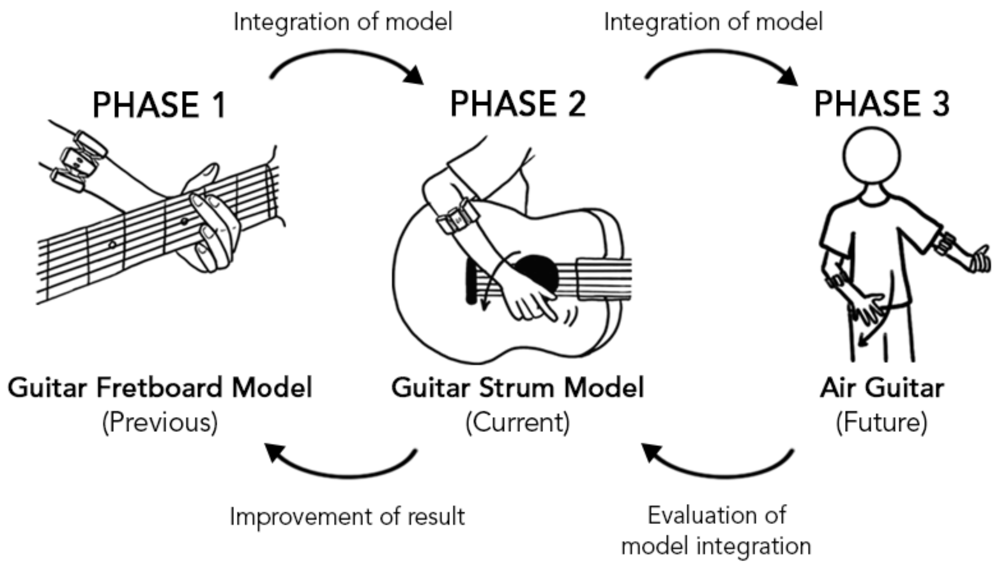

Figure 1. The Augmented Guitarist Project showing its different phases

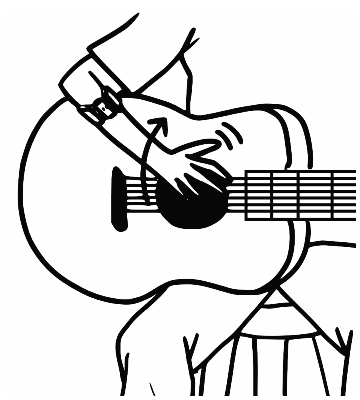

Figure 2. The Position of the Guitarist in Performing an Upward and Downward Strum Motion

we were able to discover their insights regarding the use of Myo as an alternative medium for performing. We believe that these gathered insights from the study participants were inclined towards a more personal guitar experience rather than in an exposed setting. We believe that we may need to improve our model and prototype and to conduct a thorough user study to refine and validate our results.

Model Building

We employed a k-Nearest Neighbor classifier in order to train a model that can identify the type of strum gestures. In order for us to classify a strum sample as either up or down, we calculated the distance against all other training samples, along with a prediction made according to a "majority vote" by the k-nearest training samples to the test sample.

$$DTW(X,Y) = \min_{W} \left\{ \sum_{k=1}^{K} d_k, W = \langle w_1, w_2, ..., w_K \rangle \right\} \quad (1)$$

Dynamic Time Warping (DTW) (as seen in Equation 1 as explained by [8]) was chosen as the distance metric employed by the nearest-neighbors classifier. DTW is considered to be an effective method for time-series classification as it takes into account the temporal dependency of the time series features [15]. The difference in duration length of various samples were also considered. The distance of a test sample against a training example was taken by computing the DTW of the test sample's eight EMG features against the training example's eight EMG features. This yielded eight distance values, corresponding to the DTW of EMG feature 1 to 8. The Root Mean Square (as seen in Equation 2) of these eight values is taken and is used as the final distance metric in the k-Nearest Neighbors algorithm.

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + ... + x_n^2)} \quad (2)$$

We developed the model, imported and split the data into training and test sets, and then retrained the model. The accuracy, kappa statistic, and root mean squared error (RMSE) were taken afterwards to assess the performance of the model.

Data Collection & Analysis

We performed two distinct phases of data analysis: specifically for the model and for measuring user insights. The Myo armband yields five datasets per strum sample, namely: electromyography data (EMG), gyroscope data, orientation data, accelerometer data, and euler function data. The EMG data is made up of eight (8) time series features corresponding to the Myo's eight EMG channels. Only the EMG data's eight channels were used as features in building the learning model. In terms of gathering user insights, we deployed the provided questions earlier and acquired their inputs. These were collated, and performed descriptive statistical analysis to find trends and patterns in both their qualitative and quantitative responses.

Table 1. User Insights Collected

Question	Agree	Disagree
Q1. I am comfortable using the Myo armband over the actual guitar	50 %	50 %
Q2. I can practice more using the Myo armband over the actual guitar	20%	80%
Q3. I prefer the Myo armband over the actual guitar when playing in front of an audience	20 %	80 %
Q4. I am not afraid in using the Myo armband in front of an audience	80 %	20 %
Q5. I prefer using Myo armband over the actual guitar in playing the instrument itself	30 %	70 %
Q6. I consider Myo armband to be a good alternative in playing the instrument, but not an entire replacement of an actual guitar	80 %	20 %
Q7. I appreciate more the playing of music when using the Myo armband over the actual guitar	30 %	70 %
Q8. I believe that it is harder for me to use the Myo armband over playing the actual guitar	80 %	20 %
Q9. I view the Myo armband as a consumer and marketable device	80 %	20 %
Q10. I prefer to invest on a Myo armband over an actual guitar	20 %	80 %
Average	**49%**	**51%**

	Model Results		
Model	Accuracy	Kappa	RMSE
k-Nearest Neighbors (kNN)	0.46	0.37	0.73

Table 2. k-Nearest Neighbors model results

RESULTS

In this section, we present our findings in two parts namely: (1) model building and (2) feedback/insight collection.

We present the findings during the model building stages after performing machine learning tasks. We created the initial model using a k-Nearest Neighbors classifier with Dynamic Time Warping (DTW) used as the distance metric in order to account for the temporal dependence of the features, and the difference in length of the samples. The accuracy, kappa statistic, and root mean squared error (RMSE) of the model were taken after the training phase. See Table 2. We believe that the below average results contribute to the fact that there was not enough data to begin with modeling the classifier. However, the kappa statistic of 0.37 (which is borderline acceptable) states that the features are acceptable and agree with each other. An accuracy score of 0.46 means that the model will correctly predict forty-six (46) out of one hundred (100) strums. While the model had an acceptable kappa and accuracy score, it will not perform well in a real world setting. We were not able to perform Feature Extraction, and Attribute Evaluation which could have increased the kappa score. As such, further tuning and analysis can still be done to improve the accuracy value of the model.

After validating our survey data, we discovered that the responses were nearly split with an average of 51% preferring an actual guitar over the Myo armband. We found that guitarists still value the touch and feel of an actual guitar to be able to play a song together with its rhythm. With questions Q2, Q4, Q5, Q7 and Q8 from the survey (See Table 1), it shows that the playing of the instrument itself is already good and accepted in terms of its overall usage. However, most of the guitarists have emphasized that they also view the Myo armband as a good alternative for the instrument with 80% agreeing in question Q6. This was then verified in the interview as they mentioned that the sensation of playing the guitar cannot be mimicked by the Myo armband, thus it should not replace the guitar completely, but rather serves as a good alternative over the actual guitar. In contrast to this, we have also found that some guitarists still view the Myo to be an entirely innovative product that can totally change the way we play music. Most of them believe in the possibility of having the air guitar model be more appropriate to use than the actual guitar. One of the reasons they mentioned is that when they need to carry a guitar and use it for long hours, the Myo armband would be an appropriate use for them. They have also mentioned that the Myo armband would be better if implemented with a virtual reality headset.

As learners could have easily visualize what is going on and able to respond with a guide of an application. There are also insights towards the positive impact of the Myo armband from a point of view of a guitarist with fifteen (15) years of experience and loves to write musical notes. As the Myo armband supports the possibility of integrating the playing of the guitar and the writing of notes simultaneously, it would help experts in the field to easily manage writing their notes. More responses were also analyzed, and it is towards their view about the Myo armband in general. Most of the guitarists stated that the ability of the device and the concept itself is more inclined for musical professionals , especially individuals who play the guitar for acoustic recording at a studio. With all of the device features, they mentioned that it would be more marketable in the future , but since it is still in the research phase, they still prefer on what they are used to which is the playing of the actual guitar. With 80% disagreeing in question Q10, the Myo armband is still viewed to be just an alternative, but it is also considered by many to be a good consumer and marketable device in the future with 80% agreeing in question Q9. One of the guitarists have stated that it is like a "backward" innovation that is common in big companies nowadays, where they innovate a product removing its naturality in terms of overlaying the basic components and implementing an entirely new and more salable module.

The potential of the Myo armband is there and can simply be as good and as comfortable to use just like an actual guitar with equal percentage result in question Q1. As most of the guitarists believe that the Myo armband would be the next thing in musical interaction, definitely the Myo itself can offer a lot of advantages in variety of fields if implemented properly.

With at least 30% of guitarists agreeing in question Q7 and 80% disagreeing in question Q3, they still indeed prefer the guitar based from its normal structure, to play the guitar in a natural way.

CONCLUSION AND FUTURE WORK

We have introduced a framework for an augmented computer guitarist by integrating EMG as an input source. There has been early work on classifying guitar chords. In this study we have covered Phase 2 of the defined project roadmap which created a guitar strum classifier. However, below average results mean that we can further improve the accuracy scores by having a larger data set. Since feature extraction has not been considered in this study, we recommend techniques that slice the data into more fine grained segments and features similar to what has been done in the works of [3, 1, 2]. In terms of the overall project roadmap, we intend to design and develop a prototype that can recognize both guitar chords and user strums, integrating the models after some fine tuning. By doing this, we can use a synthesizer that will allow the user, in a two-arm EMG setup to actually *air guitar* and produce music from its natural gestures. We intend to research further and improve this setup so that the design fits the actual needs of its target participants. Future work would involve having a bigger data set, a locale, and a more complex machine learning task in order to improve overall user experience.

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REFERENCES

1. BRUDERLIN, A., AND WILLIAMS, L. Motion signal processing. In *Proceedings of the 22nd annual conference on Computer graphics and interactive techniques* (1995), ACM, pp. 97–104.
2. CHEN, X., ZHANG, X., ZHAO, Z.-Y., YANG, J.-H., LANTZ, V., AND WANG, K.-Q. Multiple hand gesture recognition based on surface emg signal. In *Bioinformatics and Biomedical Engineering, 2007. ICBBE 2007. The 1st International Conference on* (2007), IEEE, pp. 506–509.
3. DEJA, J. A., BLANQUERA, K., CARABEO, C. E., AND COPIACO, J. R. Genre classification of opm songs through the use of musical features. In *Theory and Practice of Computation: Proceedings of Workshop on Computation: Theory and Practice WCTP2014* (2016), World Scientific, pp. 77–88.
4. DEJA, J. A., TOBIAS, J. P., ROQUE, R. C., DAVID, D. G., AND CHAN, K. G. Towards modeling guitar chord fretboard finger positioning using electromyography.
5. GRICE, E. A., KONG, H. H., CONLAN, S., DEMING, C. B., DAVIS, J., YOUNG, A. C., BOUFFARD, G. G., BLAKESLEY, R. W., MURRAY, P. R., GREEN, E. D., ET AL. Topographical and temporal diversity of the human skin microbiome. *science 324*, 5931 (2009), 1190–1192.
6. HIGGINS, K. M. *The music between us: Is music a universal language?* University of Chicago Press, 2012.
7. LARSEN, J. V., OVERHOLT, D., AND MOESLUND, T. B. The actuated guitar: A platform enabling alternative interaction methods. In *SMC Proceedings of the Sound and Music Computing Conference* (2013), Logos Verlag Berlin Stockholm, Sweden., pp. 235–238.
8. LI, Y., CHEN, H., AND WU, Z. Dynamic time warping distance method for similarity test of multipoint ground motion field. *Mathematical Problems in Engineering 2010* (2010).
9. LIAROKAPIS, F. Augmented reality scenarios for guitar learning. In *TPCG* (2005), pp. 163–170.
10. MALLOCH, S. E., AND TREVARTHEN, C. E. *Communicative musicality: Exploring the basis of human companionship.* Oxford University Press, 2009.
11. NYMOEN, K., HAUGEN, M. R., AND JENSENIUS, A. R. Mumyo–evaluating and exploring the myo armband for musical interaction.
12. PACHET, F. The continuator: Musical interaction with style. *Journal of New Music Research 32*, 3 (2003), 333–341.
13. PHILLIPS, M., AND CHAPPELL, J. *Guitar for Dummies*. 2006.
14. SACHS, C. *The history of musical instruments*. Courier Corporation, 2012.
15. YU, D., YU, X., HU, Q., LIU, J., AND WU, A. Dynamic time warping constraint learning for large margin nearest neighbor classification. *Information Sciences 181* (2011).