EMGuitar: Assisting Guitar Playing with Electromyography

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ABSTRACT
Mastering fine motor tasks, such as playing the guitar, takes years of time-consuming practice. Commonly, expensive guidance by experts is essential for adjusting the training program to the student's proficiency. In our work, we showcase the suitability of Electromyography to detect fine-grained hand and finger postures in an exemplary guitar tutor scenario. We present *EMGuitar*, an interactive guitar tutoring system, that assists students by reporting on play correctness and adjusts playback tempi automatically. We report person-dependent classification utilizing a ring of electrodes around the forearm with an F1 score of up to 0.89 on recorded calibration data. Furthermore, our system was received well by neither diminishing ease of use nor being disruptive for the participants. Based on the received comments, we identified the need for detailed play accuracy feedback down to individual chords, for which we suggest an adapted visualization and an algorithmic approach.

ACM Classification Keywords
H.5.m Information interfaces and presentation (e.g., HCI): Miscellaneous.

Author Keywords
Electromyography; posture detection; fine motor tasks; assistance system.

INTRODUCTION
When interacting with the physical world we predominately use our hands to manipulate objects and tools at our disposal, yet correct execution of fine motor tasks such as learning how to play an instrument often requires training that may take up to several years depending on the student's affinity. Individual supervision by experts is often expensive and requires effort, which gives rise to the idea of sensor-based assistance systems that may alleviate the need for supervision.

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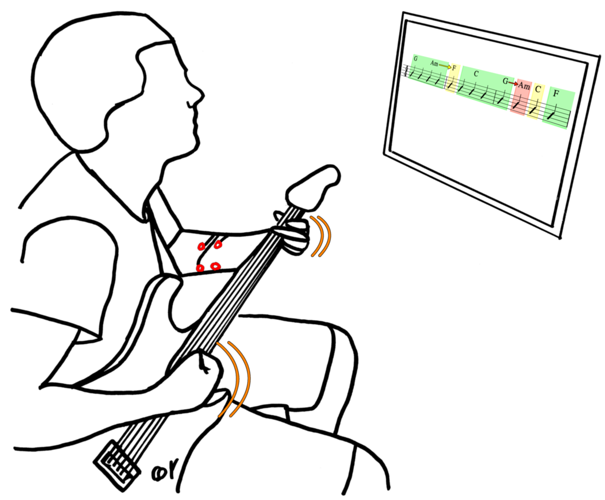

Figure 1. User interacting with *EMGuitar* (chord visualization is not part of the prototype). Muscle activity is being recorded by electrodes on the forearm (red).

Such systems evaluate task execution and can provide assistance if necessary. In the domain of music education, researchers have already experimented with different modalities for feedback and assistance. In *guitAR* [5], Löchtefeld et al. showed an augmented reality approach to depict correct finger position on a guitar fretboard, while *MusicJacket* [4] employed a vibrotactile jacket to inform users of bad posture during violin play.

In this work, we evaluate the feasibility of Electromyography (EMG) as a sensing modality to detect domain-specific fine motor tasks and facilitate action detection in a guitar tutoring scenario. This concept of muscle-computer interfaces (muCIs) has already been researched in the context of gesture recognition [9]. Previous research has shown that finger movements and specific gestures can be detected effectively using Electromyography under different recording scenarios (10 electrodes setup [9] vs high-density grid with 192 electrodes [1]). We investigate if EMG is not only feasible as an explicit input method by invoking defined gestures, but can be used implicitly as well.

For this purpose, we draw on musician-instrument interaction and aim to recognize played chords during a guitar playing session. We believe that playing chords on the guitar is a representative case for many fine motor tasks, because it mainly consists of isometric muscle activation[1], which is easily recognizable with Electromyography [6, 12]. Furthermore, different playing styles allow to assess the feasibility of this technique in scenarios with high variance, i.e. achieving the same result (chord sound) with varying postures (different chord grip).

To verify the applicability of EMG in interactive assistance systems, we created the guitar tutoring system *EMGuitar* and deployed it in a study with seven participants to evaluate its accuracy in a real-world scenario including cross-session and inter-person detection of chords.

We contribute that (1) Electromyography can be used successfully and deliver real-time input for an interactive system that detects fine motor tasks, such as playing the guitar. Additionally, we found that (2) adequate and timely feedback during the learning process is desirable.

EMGUITAR: A GUITAR TUTORING SYSTEM

A guitar tutoring system should be able to assess the student's play accuracy in real-time and respond accordingly. If this is technically feasible, how can we design for adequate feedback that supports the learning process? In this paper, we want to answer the question whether such a system is able to provide automatic tempo adjustment during the learning phase or if manual adjustment is to be preferred.

Scenario

Our tutoring system detects the player's proficiency by evaluating how accurately a given chord progression was executed. If the player is comfortable with the current song tempo, chord accuracy will be high and the system increases the tempo. If the chosen tempo is too fast, the player will struggle to finger the chords correctly, hence accuracy will diminish. The system reacts by slowing the tempo for the next iteration. During the study, we analyzed how musicians interact with *EMGuitar* and which requirements and problems arose when they used the system.

Apparatus

We used the BrainVision actiCHamp EEG recorder[2] with active surface electrodes to perform EMG sensing. Individual finger movement is the result of multiple muscles working together [11], hence, we utilize a ring of electrodes around the forearm to capture the majority of the involved muscle activity. In total, we applied ten electrodes around the participants' left upper forearms. This included one ground (GND) and one reference (REF) electrode, minimizing noise levels. The remaining eight data channels were sampled at $500\,Hz$[3].

The electrodes were attached in a ring-like fashion around the arm using adhesive foil rings as shown in Figure 2. Afterwards, each electrode was injected with conductive gel and checked for impedance.

Figure 2. Electrode configuration with two rings around the forearm each consisting of five electrodes.

The recorded data was transmitted via USB to the Recording PC and redirected as a data stream into the local network. On the other side, the Stimulus PC was presenting chord patterns on a 27 inch LCD monitor, while simultaneously sending a marker stream into the network. Both streams were locally time synchronized on the Stimulus PC using the *Lab Streaming Layer (LSL)*[4] framework and saved to its hard drive.

Methodology

We closely follow related work ([6, 9]) with regard to preprocessing[5] and feature extraction[6]. In a preliminary evaluation with three participants we found that the RMS (root mean square) feature groups performed best with a given epoch size of $250\,ms$ when tasked with classifying seven different chords[7].

Since the system is aimed at beginner guitarists, we reduced the set of chords to C, F, Am and G. This set of chords forms the *I-V-vi-IV-progression*, which is heavily used in pop music. By including the barre chord F, we introduced a challenging chord for beginners as well.

We employed a within-subject design with two conditions; the first with manual tempo adjustments by the participants, the second with the tempo adjusted by the system. To counteract learning effects due to repetitive chord changes, we created two chord sequence patterns (A and B) out of all possible permutations of the above chords. Each chord appeared 12 times in each pattern, while their duration was randomly assigned from one to three beats. A pattern consisted of 20 bars; each containing four beats. For calibration, we tasked the participants to play two bars of each chord twice.

The tempo adjustments were made between 40 BPM and 90 BPM. Tempi lower than 40 BPM were hardly playable, while 90 BPM was challenging if chords changed as often as every beat. Based on test runs, we chose the following mapping for the new tempo: $\min(90, \max(40, p + (a - 0.5) \cdot 100))$, where p is the previous tempo and a the estimated chord accuracy of the player.

[1] Continuous muscle activity without visible movement.

[2] http://brainvision.com/actichamp.html

[3] The recording system is able to sample at much higher rate. However, related work [7] states that most power of the signal is within $5\,Hz$ and $250\,Hz$.

[4] https://github.com/sccn/labstreaminglayer

[5] Segmentation into epochs; Bandpass filter between $2\,Hz$ and $100\,Hz$; Bandstop filter between $49\,Hz$ and $51\,Hz$.

[6] Features are calculated as described in [9].

[7] Up to 0.87 F1 score for person-dependent classification.

Since chord changes might happen every beat, we chose to neglect one epoch ($250\,ms$) at the end of each chord change. To further counteract noise due to chord-change artefacts, we set up a majority voting as a post-processing step.

Participants

We recruited eight participants from the University of Stuttgart through mailing lists. The data of seven (1 female, $\bar{x} = 22.6\,y$, $SD = 2.3\,y$) were used for further analysis[8]. All participants were beginners on the guitar and reported normal sight and hearing. They were able to play the four chords. After the experiment, each participant was paid an allowance of 10 Euro.

Procedure

After introducing the prospective participants to our study, we handed them a detailed study description, stating that they were to play a given chord sequence with the guitar during several iterations. Playback, provided by a metronome, would be adjusted either manually by the participants or automatically by the system. Participants were made aware that adhesive electrodes would be placed on their forearm and their muscle activity would be recorded. After providing informed consent, the participants were asked to complete a demographic questionnaire, polling sex, age, work field, highest educational qualification, their eyesight and general health. The experimenter was present to answer any questions.

Before the experiment started, the experimenter placed electrodes on participants' forearms. They were then given time to familiarize themselves with the provided guitar. Subsequently, we conducted a first calibration at 40 BPM followed by a first run consisting of five repetitions of either pattern A or B and intermediate tempo adjustments between repetitions. Adjustment were either made manually or automatically. The last repetition was always executed at 90 BPM, ensuring the same end tempo for each participant. After a short break, another calibration was conducted followed by five repetitions using the other experiment condition.

At the end of the experiment, we asked the participants to fill out two identical questionnaires, one targeting the manual condition and one for the automatic condition[9]. The questionnaires contained questions (7-point Likert scale) based on the work of Yuksel et al. [14] and their piano tutoring system. These questions were aimed at the learning process and mastery of the piece (cf. Figure 3). A third questionnaire was specifically tailored to the automatic condition where we asked the participants the questions listed in Table 1 (5-point Likert scale and free text). The whole study including setup and electrode placement did not exceed 60 minutes. Ethical approval for this study was obtained from the Ethics Committee at the University of Konstanz.

Results and Discussion

In this section, we will discuss the results from our questionnaires and their implications. Additionally, we will assess classification performance and its influence on the tutoring system.

Question
Please rate your perceived accuracy of the system in evaluating your performance.
How did you perceive the tempo adjustments the system made?
How challenging were the system's tempo choices?
Did the electrodes limit you in playing the guitar?
Would you use the system to learn to play guitar? Why or why not?
Imagine the system/electrodes could be integrated into your garments. How does this change your perceived usability of the system?
Further comments

Table 1. Questionnaire for the automatic condition.

Questionnaires

We compared the answers for the automatic and manual conditions from the first two questionnaires. A Wilcoxon signed-rank test showed that the reported Likert scores for all four questions were not significantly affected by the condition the subjects were using. The results are illustrated in Figure 3.

However, the results of the first two questionnaires (cf. Figure 3), indicate that the participants were comfortable with either tempo adjustment. We believe that the automatic system gave the participants a feeling of security as it relieved them from having to choose a new tempo, which was lower on average for the automatic condition[10]. However, answers for "How enjoyable was it to learn the piece?" suggest that the manual condition was more enjoyable for the subjects. We believe, that this can be explained by the low accuracies reported by the system and might have irritated the subjects. Nevertheless, participants stated that the electrodes did not limit them during their guitar play in the third questionnaire[11].

We analyzed the textual feedback provided by the users in the third questionnaire using affinity diagramming with two researchers identifying themes in the qualitative data. We found that users perceived an increase in playing accuracy:

> *"The given tempi helped to challenge me in play more quickly but still accurately."* [P7]

Further, users were able to realize, reflect upon and rectify possible flaws in their playing style:

> *"Yes, because my own adjustment was probably too high, the system probably is more realistic."* [P2]

EMGuitar was also perceived as offering a playful experience and the opportunity to practice alone while still receiving feedback was welcomed by the users:

> *"Yes because it's fun and it has the self-learning aspect into it without having a teacher to keep telling me what to do."* [P3]

[8] We believe this to be a meaningful sample size for our formative evaluation since all participant are familiar with the instrument [3].

[9] Since the electrode cables limited their writing capabilities, we opted to get feedback at the end for both conditions.

[10] Automatic: $\bar{x} = 57$, $SD = 18$; Manual: $\bar{x} = 66$, $SD = 12$; all BPM.

[11] Only the lowest two values were given as answers.

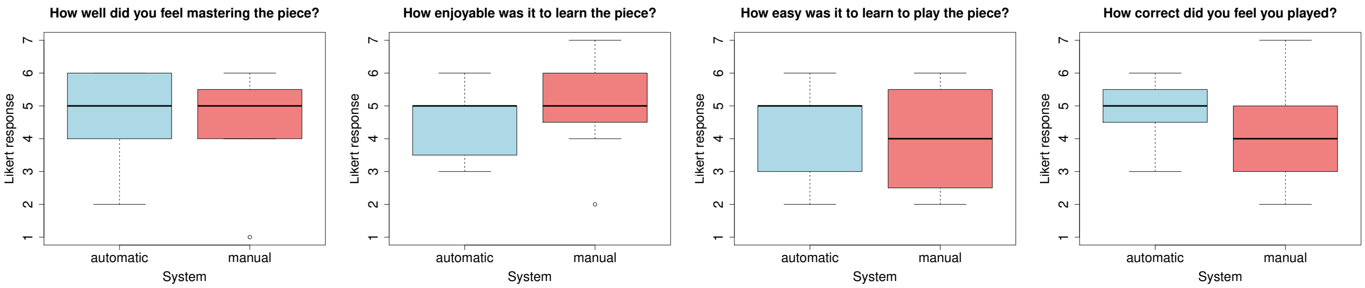

Figure 3. Boxplots illustrating the results of the first two questionnaire, reaching from lower to upper quartile. Whiskers mark the furthest observation within a distance of 1.5 times the box size. Outliers are marked with small circles. Questions are adapted from the work of Yuksel et al. [14].

In the free text comments, the subjects asked for more sophisticated feedback like chord and chord-change highlighting. This matches with our vision of the system and encourages further development. Figure 4 shows a possible visual feedback.

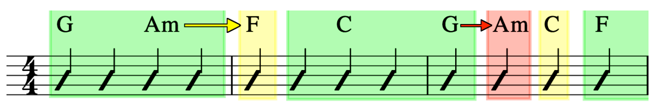

Figure 4. Possible feedback visualization for chord grips and chord changes. Colors range from green (flawless play) to red (faulty play).

Intra-Person Performance

To assess person-dependent performance during the experiment, we utilized the recorded calibration data. We report F1 scores[12] for training and testing on either calibration, respectively, yielding an average F1 score of 0.89. To evaluate the degradation of accuracy due to electrode location shift and sweating, we additionally trained on the first calibration set and tested on the second[13], only reaching an F1 score of 0.59 ($min = 0.25$, $max = 0.72$).

We have shown that detection accuracy is high when calibrating just before the evaluation. Yet it is also evident that performance can degrade quite fast after half an hour of playing time, mostly due to electrode shifts and impedance changes. Hence, repetitive calibration is necessary and hinders usability. We believe that tailored sensing wear, such as gloves and sleeves, will alleviate this issue, allowing for a tight fit.

Estimated chord accuracy when playing either pattern A or B ranges between 30% and 70%. While this can be attributed to the player proficiency, quick chord changes at high tempi introduce artefacts in the signal chain. We believe that detecting chord changes, e.g. using hidden Markov models, can remedy this problem and also provide feedback on flawed changes (as explained in Figure 4).

Inter-Person Performance

Inter-person performance was evaluated using a leave-one-subject-out approach. Furthermore, we applied a principal component analysis (PCA) before learning. This technique can help to compensate inaccurate electrode placement across participants and has been applied to EMG signals before [15]. The unmodified evaluation shows F1 scores ranging from 0.10 to 0.46, rendering the approach unusable for a tutoring system. PCA-modified evaluation shows similar values (0.10 to 0.3), yet only relying on nine principal components[14]. These findings suggest that dimensionality reduction techniques are effective and suitable for EMG-based detection, effectively reducing the feature space. However, current performance is not satisfactory for a tutoring system. A person-dependent calibration is still essential. Independent component analysis (ICA), as shown by Naik et al. [8], might be a method to tackle this challenge, revealing the contribution of specific muscle fibers and applying automatic re-calibration.

CONCLUSION

In this paper, we have showcased the feasibility of detecting fine-grained hand and finger postures using Electromyography in a guitar playing scenario. Our system *EMGuitar* was received well as it neither diminished ease of use nor was disruptive for the participants. Automatic tempo adjustment was neither better nor worse than manual adjustment by the participants. However, they expressed the need for more fine-grained feedback on play accuracy down to individual chords as opposed to mean scores per song. We conclude that it is more favorable to design for intermediate and detailed feedback. Here, we suggest an adapted visualization as well as an algorithmic approach to realize this. It remains to be researched which feedback modality – visual, audio or tactile – works best in this case to maximize the learning effect.

We envision the use of electrode bands as a natural sensing modality in tutoring systems. Especially since sensing electrodes can be easily integrated into garments and wearables, allowing for widespread deployment including playful interaction (*YouHero* [2], *Air-Guitar Hero* [10]) as well as natural interaction [13] with the instrument.

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[12] Grouped k-fold cross validation using an SVM classifier.

[13] Conducted approximately 20 minutes later.

[14] Instead of 36 dimensions for the unmodified version.

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