# Electrical Muscle Stimulation to Improve Temporal Precision During Rhythm Learning

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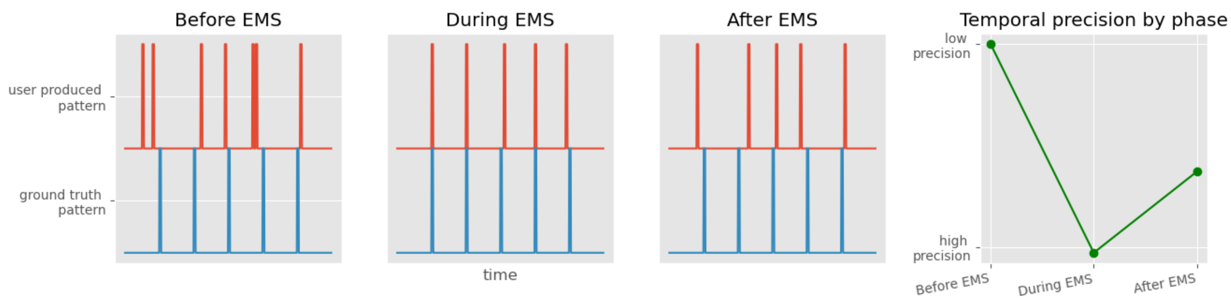


**Figure 1: Fabricated data showing improvement in temporal precision after training with our EMS prototype. Spikes indicate note onsets.**

## ABSTRACT

Various supporting tools have been used to provide a scaffold during motor learning and music learning, e.g., a metronome for timekeeping during practice. Electrical muscle stimulation (EMS), where muscles are actuated via non-invasive skin electrodes, helps with motor learning across domains; however, EMS has not been systematically explored for rhythm learning. Motivated by neuroscientific theories of motor learning, this work presents a prototype of a novel interface that aims to hasten the user's learning of rhythmic patterns using EMS. To evaluate how proprioceptive, tactile, or auditory training display modalities enhance user learning (as indexed by temporal precision), we will test subjects under three conditions: (1) actuating-EMS to support tapping to the rhythm, (2) tactile-EMS, where the rhythm plays through low-level stimulation, and (3) no-EMS (audio only). We additionally introduce a new method for evaluating rhythm difficulty so as to examine effects between difficulty and display modality. In the future, we will further develop our neuroscientific theory-based design approach to investigate user performance-sensitive training modes.


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## CCS CONCEPTS

• **Human-centered computing** → *User studies*; *Haptic devices*; *Empirical studies in HCI*.

## KEYWORDS

rhythm learning, musical interface, electrical muscle stimulation, musical haptics

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## 1 INTRODUCTION

Mastering a musical instrument requires years of technical practice. Development of good technique, sight-reading abilities, and knowledge of music theory are required to improvise, learn, and compose new pieces. Improvement via repetitive practice is enabled sensorimotor learning, whereby motor behavior is adjusted based on sensation to optimize an outcome, i.e., playing a target musical sequence. A practiced pianist has acquired predictions about the auditory consequences of the movements of their fingers. Specifically, to learn mechanisms of predictive control (such as a movement sequence), a forward model of a planned movement is thought to be computed by the brain. The predicted sensory consequences of the movement are compared to sensory information to evaluate movement success and corrective changes, as in error-based learning [22]. If a wrong note is played, the ensuing dissonant chord does not match the expected harmonious chord. They may then register a wrong note and fix it. Learning predictive control schemes is then key to executing a sequence of movements precisely in time, such as playing a rhythm. Recent innovation in technologies that interface directly with the body affords HCI researchers the novel ability to directly shape sensory feedback [10]. This enables the tuning of the forward model so as to shape the motor learning process of musical practice.

Electrical muscle stimulation (EMS) is one such body-interface technology. First developed as a rehabilitation treatment, EMS systems electrically stimulate muscles via non-invasive skin electrodes causing involuntary contraction. The ensuing change in muscle length is sensed by the brain via proprioception whereby stretch signals from muscle spindles form a percept of limb location. Indeed, early adaptation of EMS into HCI relied on the concept of proprioceptive interaction [11]. As proprioception is the sense of the body position in space, this modality lends itself to spatial display. Motor learning applications of EMS in HCI have therefore been mostly proprioceptive displays with the aim of demonstrating to the subject the correct sequence of postures or movements in space [3, 5, 18], or muscles to activate [14]. While spatial control of the hand with EMS has seen recent improvements [[15], [17], [9]], use of EMS for temporal learning has been limited. EMS can actuate the body with millisecond-level precision, augmenting the temporal precision of normal motor control. Such reliable temporal control could augment rhythm learning. Learning the precise timing used in rhythm production and replication is an essential aspect of learning music.

Whether proprioceptive feedback generated from EMS-triggered actuation can speed up rhythm learning remains unexplored. We therefore propose to test EMS-enabled proprioceptive display for rhythm learning via a study design inspired by Kasahara et al., 2021, who use a pre- during- post- approach with three experimental conditions [8]. Here, we implement a series of rhythm production tasks across three experimental conditions for rhythm display - actuating-EMS: the subject is stimulated to tap along to the rhythm, tactile-EMS: the subject is lightly stimulated (but not actuated) along to the rhythm, and no-EMS (only audio). For each condition, we evaluate the increase in temporal precision as indexed by the earth mover's distance between the subject-produced rhythm and the ground truth rhythm. Improvements for each condition will yield insight as to the potential for proprioceptive display via EMS for enhanced rhythm learning.

## 2 RELATED WORK

Holland et al., 2010 detailed a vibro-tactile rhythm display system that aided users in playing polyphonic rhythms on a drum kit, dubbed, the 'Haptic Drum Kit' [6]. They conducted a user study to determine which display modality would appeal most to users and found that users preferred audio and haptic display together over audio or haptic display alone. Similarly to the EMS system presented here, the Haptic Drum Kit was designed to induce entrainment to a set of rhythms, where the vibro-tactile stimulation was a rhythm display rather than a cue for user response. We build on the Haptic Drum Kit in that our system makes use of the proprioceptive modality via EMS. Furthermore, we index rhythm difficulty and its effects on improvement by display modality and quantitatively examine performance relative to ground-truth rhythms.

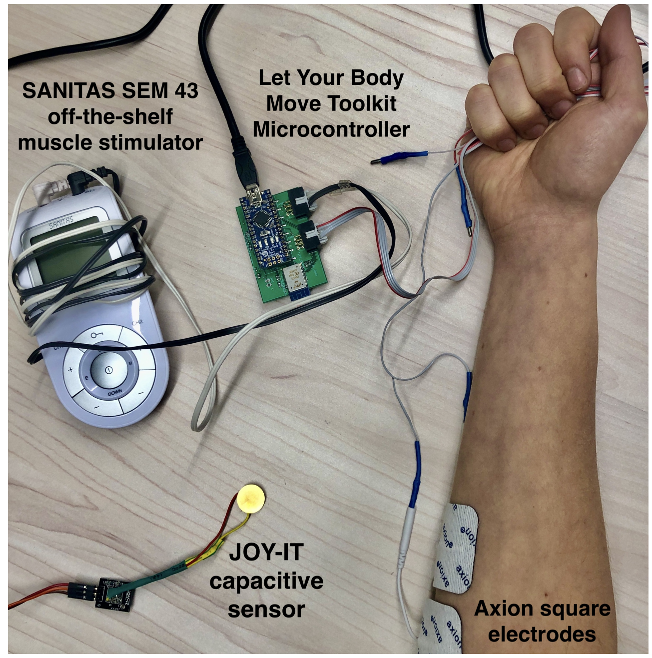


**Figure 2: We use an EMS toolkit to implement a rhythm training apparatus [16]. The subject trains with the EMS-triggered proprioceptive display. Performance before and after training is measured using the capacitive sensor.**

Goto et al., 2020 introduce a system of pneumatic actuators for proprioceptive display that train a user to improve two-handed rhythm performance [4]. They tested subject performance after training on 'easy', 'medium' and 'hard' rhythms, comparing between improvements due to training with audio versus proprioceptive display. They found performance improved more with the actuators than with audio training. Our study builds on this work in that instead of mechanical actuators which indirectly stretch the muscle due to imposed limb movement, we use EMS, where the muscle is stimulated to contract. These factors may further enhance the proprioceptive display in that with EMS, the subject often cannot tell whether they moved their hand or EMS did. EMS may then augment a subject's timing while respecting their sense of agency [7]. This can help with motor learning itself: EMS actuation of the subject's limb close in time to self-generated motor commands results in more improvement than actuation well before the motor command [8]. This suggests EMS provides a better proprioceptive display for motor learning than imposed proprioceptive displays such as mechanical actuators, although this has yet to be proven outright.

Ebisu et al., 2016 describe a pertinent EMS rhythm display system, 'Stimulated Percussions,' which writes rhythms to the body as in our implementation [2]. They tasked users to play a 3:4 polyrhythm before and during EMS and showed EMS actuates users more accurately in time than baseline. We build on Stimulated Percussions

| Rhythm name | Rhythm string |
|---|---|
| "to the beat" | 1000100010001000 |
| "syncopated" | 0010001000100010 |
| "three over four" | 1001001001001000 |
| "lunch room beat" | 1000100010100010 |
| "hard rhythm 1" | 0100100001001000 |
| "hard rhythm 2" | 0100100010000010 |
| "hard rhythm 3" | 0010001001000001 |

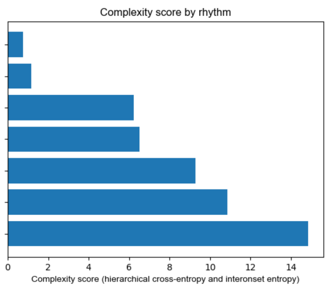


**Figure 3: Rhythm stimuli are presented (left) and indexed for complexity by combining metrical hierarchy cross entropy and interonset interval entropy [12, 19] (right).**

in that our study examines post-EMS-training performance to support conclusions on motor learning (rather than only during-EMS training) and we compare effects in audio and tactile modalities.

## 3 MATERIALS AND METHODS

The proprioceptive rhythm display system was ed using the Let Your Body Move Toolkit [16]. The toolkit consists of an Arduino microcontroller that modulates the voltage of an off-the-shelf functional electric stimulation system (SANITAS) and delivers the stimulation to skin electrodes on the ventral forearm on the subject's dominant side (2). To sense performed rhythms, subjects tapped a capacitive sensor, the trace from which is converted to contact onset times.

The six rhythms we chose and the tempos at which they were presented are represented in Figure 3. These rhythms were selected to sample from a broad set of rhythm types and span a range of rhythm difficulty. Rhythms are represented as binary strings where a 1 indicates a note onset and a 0 indicates no onset. We use the 'Hierarchical Position Model' to characterize rhythm commonality which measures the modified cross-entropy of a rhythm sequence by calculating the probability of each note onset based on its rhythmic context (hierarchical position) [19]. This model out-performed other models in predicting the rhythms from Western folk and classical melodies. The model yields an estimate of rhythm string probability by multiplying the probabilities of each onset or lack thereof, conditioned on rhythmic context. Temperley's index is defined as follows:

$$-\log(p(S))/N = -\frac{1}{N}\sum_{n=0}^{n=N-1}\log(p(S_n|c_n))$$

where $S_n$ is the binary digit at position $n$,$N$ is string length, $c_n$ indicates the context of the note at $n$ (corpus-measured prior according to 'anchoredness' of the note relative to higher metrical positions - see [19]) from 0 to N in the measure.

One weakness of this index is that it does not consider sequence repetitiveness. Hence, the sequence $S = 0101010101010101$ has a high entropy score (low probability) as the onsets fall at unusual locations, even though $S$ has only one interval to be learned. To correct this, we multiply a string's modified cross-entropy with its interonset interval entropy, which is the entropy of the distribution of onsets in a rhythm string [13]. Thus this new metric incorporates the commonality of a rhythm string and the diversity of its intervals.

To evaluate the temporal precision of participant performance, we measure the 'Earth Mover's Distance' (EMD) between performed onset times and ground truth rhythm onset times. The EMD, also known as the Wasserstein distance, measures the distance between two distributions by computing the 'energy' to transform one distribution into the other, where a moving cost is calculated depending on mass and distance moved. This measure was found to better predict rhythm similarity than other rhythm distances [21].

Each subject undergoes the three different experimental conditions: actuating-EMS, tactile-EMS, and no-EMS (audio only). Condition order is counter-balanced across the three testing days to counter training effects. Rhythms are presented in repeated phases with a metronome sounding at the first beat of every measure: first, rhythm audio looped for six repeats while the participant taps along. Then the participant taps the rhythm against the metronome alone in a testing phase for four repeats. The third phase is experimental, where according to condition, the participant is actuated along to the rhythm, or a electro-tactile display pulses the rhythm, or the audio plays the rhythm as before, for six repeats. Then, a second testing phase, where the subject again taps the rhythm against the metronome alone. Temporal precision is the earth mover's distance between ground truth pattern and performance. Improvement is the difference in temporal precision between the first testing phase (after first audio only training phase) and final testing phase (after experimental training phase).

## 4 CONCLUSION AND FUTURE WORK

This paper describes a new rhythm learning EMS interface and methods for calculating rhythm similarity and difficulty. The first step beyond prototype completion is testing to show the utility of the proprioceptive modality above tactile or audio alone in rhythm display for training. Once tested, this prototype and rhythm evaluation framework together enable new avenues of investigation for more user-sensitive and performance-sensitive training interfaces. Furthermore, this interface is the outcome of a key approach to designing intelligent music interfaces that plan to further explore: the use of neuroscientific theory as a starting point for interface design. In this case, we began by considering forward models of motor learning and aimed to shape sensory feedback by targeting proprioception.

As a second example, the 'minimal intervention' theory of motor control postulates that the motor system only acts to adjust movement patterns when deviations occur in task-relevant dimensions [20]. In an inspired approach, we plan investigate 'corrective-EMS': instead of actuating the whole rhythm during training on a loop, EMS will only actuate the user on the following repeat at the locations in the rhythm where the user made an error. Baseline proprioceptive display may be overbearing, taking control from the user, who then plays no active role in learning and becomes distracted. With corrective-EMS, users stay active during training but still gain detailed feedback: where in the sequence they failed and how they should have tapped.

A third example is inspired by two theories of motor learning: use-dependent learning and error-based learning [1]. Whereas in the former, movements are adjusted to be closer to the previous movement (showing the value of repeated practice), the latter requires the brain to model motor error and act to cancel it. Applying error-based learning to rhythm learning with EMS, rather than use-dependent learning, yields 'adversarial-EMS', where the EMS stimulates the finger's extensor in time with the rhythm while the user must hold their fingers steady and therefore must learn to counter the EMS in time with the rhythm. Improvement effects from this adversarial approach could be compared to those from traditional use-dependent learning methods.

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