Synchronizing Moving and Listening Behavior with Brainwaves via Rhythmic Hand Drumming

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Abstract

Background: The ability to synchronize movements with sounds is a complex behavior dependent on predicting the occurrence of future sounds. Simulation theories of musical beat perception posit the motor system contributing predictive information to the processing of auditory streams.

Methods and findings: In this study, we compared neural responses while subjects drummed or listened to rhythmic hand drumming. It was hypothesized that if the motor system is involved in auditory perception, then a similar pattern of motor system engagement via the beta band (20-30 Hz) of brain oscillations during both movement and listening activities would occur. We found evidence in partial support of the hypothesis, though results must be judged carefully in the context of past work based on finger tapping, given the relative complexity in motor programs for drumming versus tapping. We also found differences in mu rhythm (8-13 Hz) power while drumming, which is associated with drumming expertise.

Conclusions: Experienced drummers exhibited a significantly reduced amount of mu power while drumming compared to listening to drums, whereas novice drummers enhanced their mu power while playing drums, relative to listening. This suggests a more efficient use of cortical resources by experienced brains.

Keywords: Music cognition; Motor learning; Audiomotor; Sensorimotor; Beta rhythm; Auditory perception

Introduction

How do we can synchronize our movements to sounds? Before a musical ensemble begins, members will often count aloud, or otherwise synchronize their timing. Guitarist duos listening to a metronome before playing demonstrated an increase in inter-brain phase coherence during this synchronizing phase [1]. The auditory system is preferential for synchronizing movements over the visual system [2] and dynamically modulates communication models with the motor system in pianists [3]. Listening to sounds can stimulate movement, even showing increased walking velocity in those with difficulties moving due to Parkinson's disease [4]. Many concert or club goers can attest to the ease which music can stimulate rhythmic movement, from dancing to head nodding and foot tapping. Listening to music without movement can even stimulate activity in motor cortices when listening to familiar action-related sounds sans movement [5-7]. Given these findings, the motor system may play a role in predicting the occurrence of sounds [8] through a simulation model [9]. Past work demonstrated entrainment of brain waves showing responses to rhythmic sounds, even when an expected sound is omitted [10-12]. The brain rhythms involved in responses to expected and missing sounds occupy the same frequency range as brain rhythms involved in motor planning and execution in macaques [13,14].

Functional imaging reports provide a plausible network of auditory and motor cortices to dynamically carry out musical rhythm and beat perception and production behaviors. The strength of functional connections between superior temporal and dorsal premotor cortices was modulated by difficulty of rhythmic tapping [15,16]. The strength of coupling between auditory and motor cortices in rhythm perception was also affected by musical experience [17]. Strength of activation in frontal motor, inferior parietal, and superior temporal cortices in a listening task was mediated by differences in timbre, reflective of a listener's own musical expertise with a given instrument [18]. This experience dependent network is similar to a fronto-parietal network activated by listening to newly acquired action sounds [5]. Source estimates for cortical connectivity during an auditorily paced tapping task, indicated increased coherence from brainwaves between auditory, parietal, and motor areas with dominant frequency bands centered around 10 and 20 Hz [19]. Both of these frequency bands have been reported reported in other audiomotor studies such as an increase in mu (8-13 Hz) power suppression when subjects watching an action also heard associated sounds [20] and increases in beta (20-30 Hz) power suppression when subjects listened to newly acquired action sounds [21].

Is the same brain rhythm is involved in both the perception of rhythmic sounds and in movement? From a simulation account, one could predict a similar pattern of brain oscillations within subjects when they listen to a musical rhythm sans movement, and when also moving along in time with the music. We predicted that mu and beta oscillations time-locked to sounds, would show an increase in power after sound, and activity linked to motor effects would show a decrease in power prior to an executed or heard drum hit. We tested this hypothesis using hand drumming as model behavior to compare listening and moving.

Hand drumming, while a relatively underutilized behavior in the laboratory, is a promising approach to studying auditory and motor integration. It increases the ecological validity of a laboratory task while also offering enhanced face validity to test the effects of expertise. With audiomotor tasks such as tapping, there may be cross over from experiences playing or performing as a musician or dancer, but drumming as a laboratory task can look at direct effects of experience. Simple drum rhythms can be taught to musically naive subjects in a short amount of time, and behavioral performance is easily quantifiable with recordings of drum surfaces. There are difficulties with this approach as well. For one, drumming is a dynamic activity that involves coordination of many muscle groups, making it difficult to study neurophysiologically while the subject is moving. As it is a complex behavior, there are many output variables, from coordinating right and left hand movements with multiple hand positions depending on the type of drum hit. The use of both hands can have benefits in terms of identifying neurophysiological motor activity based on hemispheric differences. However, the parameter space of auditory features is more complex than traditional stimuli used in rhythm perception and tapping studies that make use of pure tones. The different drum hits (center of drum head or edge) create different sounds, which may elicit different auditory or motor responses in the brain. Another difficulty resides with the selection of a proper baseline for neurophysiological comparisons of experimental conditions. Traditionally event related sensorimotor studies have a pre-stimulus or inter-stimulus window devoid of stimuli which is used as a baseline to compare stimulus or response induced changes. A continuous activity increases the difficulty of finding a valid, stable baseline.

In the present study, we offer solutions to these difficulties based on inferences from the audiomotor literature and novel adaptations. To capture the electroencephalogram (EEG) of a moving subject, we employed the use of a prototype EEG system that was designed by Wearable Sensing Inc. (San Diego) to be relatively insensitive to small to moderate movement artifacts. With dry electrodes, there is no concern about electrolytic gel moving and breaking contact, particularly when the electrodes are held securely against the scalp by spring loaded tension on individually swiveling mounts. This introduces another confound however; that of capturing added noise in the EEG signal in the form of electromyogram (EMG) contamination from neck and shoulder muscles. Independent components analysis (ICA) can effectively reduce this contamination through a scalp spatial filter. The baseline issue is addressed by creating a baseline value that is the mean value for a given frequency across each

epoched time window. The use of a mean baseline window is previously reported in a similar task of rhythmic tapping [22], and in study of beat perception [8].

Given the above considerations and observations from previously discussed experiments with rhythmic sounds and tapping, we hypothesized decreases in beta power (20-30 Hz) prior to drum hits with rebound increases after the hits. In particular, we hypothesized that beta oscillations would decrease in power prior to subjects hitting a drum, with rebound increases in power after the drum hit. These same post drum hit increases should also occur after listening to drum sound without moving. In the listening without moving condition, we did not expect to see the same pre-hit decrease in power. In general, we hypothesized mu (8-13 Hz) and gamma (30-50 Hz) bands would show sensitivities to motor and auditory information.

Methods and Material

Subjects

Five students from UCSD and five drummers from the San Diego area were recruited for participation (mean age 26.5 years, SD=5.9, five females, two left-handed). All drummers had at least two years of professional experience playing hand drums, and reported previous familiarity with Afro-Brazilian rhythms. Each subject was shown how to play the drum rhythm after initial consent, and had to demonstrate ability to retain the rhythm and play the correct beats with the correct hands after filling out initial questionnaires. Subjects signed consent for procedures that were approved by the UCSD Institutional Review Board.

Stimuli

This study used a variation of a hand drum rhythm belonging to a family derived from Yoruban religious rituals called 'Ijexa.' This rhythm was chosen partially for the ease of play for novice drummers, and also because it includes right and left handed hits, which should aid in identification of motor processes versus auditory processes based on hemispheric differences in the brain responses **Figure 1**. The notes are spaced unevenly which should allow for identification of brainwave components associated with individual drum hits. Little is written about this rhythm as it is part of an oral tradition. This oral method of transmitting the rhythm also results in multiple variations of the rhythm, all using the same name. In this particular instance, subjects would play three drum hits with the right hand, and one hit with the left hand.

The stimulus used in this experiment was a recording of the drum rhythm played on a djembe. These are traditionally a rope tuned skin-covered drum in the shape of a goblet from West Africa. The drum used for recording the stimulus and played by experimental subjects was a synthetic head drum made by Remo. The recording was made with the drummer listening to a metronome set at 106 beats per minute. Using audio recording and editing software (Reaper v 3.92), one measure of the drum pattern was isolated and extracted to loop for the experiment.

The loop was 10714 ms long, sampled at 44100 Hz. A track approximately four minutes and fifteen seconds long was created from this loop. This provided 150 repetitions of the drum pattern. Stimuli were presented via MaxMSP (v 4.5) through ambient room speakers that were adjusted to a comfortable level that could still be heard while subjects played the drum.
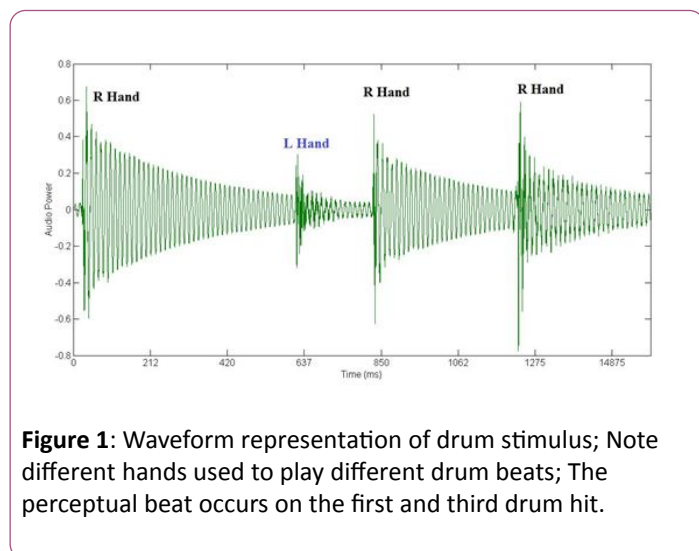

Figure 1: Waveform representation of drum stimulus; Note different hands used to play different drum beats; The perceptual beat occurs on the first and third drum hit.

Task

The experiment consisted of three phases (listen, play, and solo) and took place inside of a sound attenuated Faraday cage. First, subjects would listen to the looped recording of the drum track for approximately four minutes (150 trials) without moving. Then they would play along with the looped drum track (again 150 trials). The last phase required subjects to play the rhythm by themselves, without the recording, or other form of pacing. This phase lasted for approximately four minutes. After completing all three phases, subjects would repeat all three for a second block, resulting in about 300 trials per condition. Subjects sat upright and played a djembe that was held between the legs.

Data collection

Drum hits were registered via a piezo element affixed to the drum head, and recorded using MaxMSP. This software environment filtered out drum head artifacts and sent time stamps to the EEG system. EEG data were collected with a QUASAR DSI-24 active dry electrode prototype headset with 21 sensors placed according to the 10-20 system of electrodes (FP1, FP2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, P3, Pz, P4, T5, O1, O2, T6, L/R mastoid as reference). Each sensor was part of an array and was individually mounted within a local ground. Each array was spring loaded and mounted on swiveling arms such that they would hold tight to the scalp even when a subject moved his/her head. This significantly reduced the amount of head movement based artifacts during recording to a level that allowed drummers to not have to hold completely still for the duration of the experiment. EEG data were sampled at 300 Hz and amplified by a factor of 1000. They were recorded referenced to recording site Pz, and offline re-referenced to the linked mastoid. Data were recorded with QUASAR's Qstreamer software.

Analysis

Behavioral data: Piezo voltage recorded by the stimulus machine was saved as separate output from EEG triggers. The output of the drum triggers was analyzed in Matlab to extract relevant intervals between drum hits. A more detailed description of the method can be found in the supplementary materials. Intervals between drum hits were compared between blocks (first solo drumming compared with second solo drumming) for short term practice effects. Additionally, comparisons were drawn between drummers and novices for accuracy of interval stability.

EEG data: EEG data were analyzed using the EEGLAB [23] toolbox for Matlab. Raw data were imported and re-referenced to the mean of left and right mastoid sensors. The data were then low pass filtered under 50 Hz and initially segmented into 2600 ms second long epochs. Proper identification of time windows for the solo condition relied on an adaptive algorithm designed specifically for this experiment to seek out intervals between drum hits relative to the expected pattern plus an error window based on accumulated drift (see supplementary materials for further details). While most analyses reported here are over the 1700 ms long drum rhythm phrase, the time-frequency analysis requires longer time intervals to accurately compute low frequencies at the edges of the 1700 ms window. To assess increases or decreases in power over time, a baseline correction was performed for each epoch, deleting the mean voltage value of each time window. Epochs containing machine noise or other non-repetitive artifacts were rejected based on extreme voltage threshold detection and visual verification. Remaining data were decomposed using ICA (Infomax) to identify and remove facial and neck muscle artifacts from sensor space scalp recordings. Some neck muscle artifacts contaminated multiple components and in these cases whole epochs were removed. This cleaning procedure left approximately 200 out of 300 trials per condition per subject.

Event related potentials were calculated across subjects over the 1700 ms window, time locked to the first beat. Spectral power was also computed over the same time window, performed by a Fast Fourier Transform (FFT). Time-frequency decompositions were computed with wavelets using a Morlet taper across the 2600 ms time windows. Using a minimum of three cycles per wavelet, our lower frequency edge was 3 Hz, which allowed study of the theta band (4-8 Hz). Bandpower was estimated for both spectral and time-frequency data by integrating the power within a predefined band (theta = 4-8 Hz, mu = 8-13 Hz, beta = 20-30 Hz and gamma = 30-50 Hz) using the trapezoid rule, with a sliding integration over time for time-frequency reporting. Statistical comparisons were made using the Matlab statistics toolbox and permutation statistics included in EEGLAB. Permutation tests were chosen due to the small number of subjects included in the sample set, to control for the possibility that any one subject might unduly influence the overall mean, particularly when comparing drummers and novices. Multiple comparisons were corrected with the False

Discovery Rate threshold function [24]. Multivariate comparisons of spectral power were made with SPSS (v 20) software and multiple comparisons controlled with a Bonferoni correction.

To make a drum rhythm sample matched to the time-frequency bandpower, the envelope of the audioclip was extracted via a Hilbert transform. This was then downsampled to match the same number of samples as the EEG data, and smoothed with the default Matlab smoothing function. Since the envelope extraction into real number space lost the absolute amplitude changes in drum sample, the mean amplitude value was subtracted from the sample to normalize peaks above and below the zero point to aid in correlating to brainwaves that rise and fall above baseline.

Results

Behavioral

A 'differential drum interval' (DDI) score was calculated for each subject, which was the sum of the absolute value of the difference between the recorded stimulus drum intervals, and the observed drum intervals. This provided a single score for each movement condition (play vs solo) and each trial block (first vs second). A repeated measures ANOVA with factors of condition (2) and trial (2) with between subject factor of drumming experience and Bonferoni Correction revealed a main effect of condition that approached significance ($F_{(1,8)}=3.62$, p=0.094), but not for trial ($F_{(1,8)}=2.35$, p=0.16). Subjects drummed with greater accuracy (smaller deviations from expected intervals) during the play along condition with smaller variability (M=41.4, SD=4.2), than during the self-paced solo condition (M=57.9, SD=9.2). Subjects also showed a small improvement in drumming between the first (M=52.7, SD=6.2) and the second block (M=46.6, SD=5.9). While drummers performed better in terms of DDI than inexperienced drummers (M(drummer)=45.9 msec, SD=8.1, M(novice)=53 msec, SD=8.1), the interactions between experience and condition ($F_{(1,8)}=0.23$, p=0.65), trial ($F_{(1,8)}=0.41$, p=0.54), and condition*trial ($F_{(1,8)}=1.52$, p=0.25) were not significant.

Validation with event related potentials

As this was a novel task, and there is little precedent in the literature examining brainwaves to rhythmic drum sounds or actions, the first analyses were qualitative assessments of event related potentials. ERPs time locked to the sound of drums revealed an auditory N1 approximately 100 ms after stimulus presentation **Figure 2A**. Unlike a standard auditory ERP experiment, there was no resting baseline window prior to stimulus onset, hence the noisy pre-stimulus period. The average sound response combines different types of drum hits, and each type of drum hit could elicit different brain responses based on differences in the kinematics or frequency profile of the drum hits. Likewise, a motor effect can be seen averaged across drum hits that shows a negative deflection, potentially similar to a readiness potential initiating about 250 ms prior to the drum hit **Figure 2B**. As the drum hit should produce a sound,

the presence of a negative deflection just before 100 ms post drum hit marks the presence of an auditory response similar to what is seen in the auditory N1. We take these as evidence that auditory and motor responses to an ongoing rhythmic drumming task can be detected by the prototype EEG system.
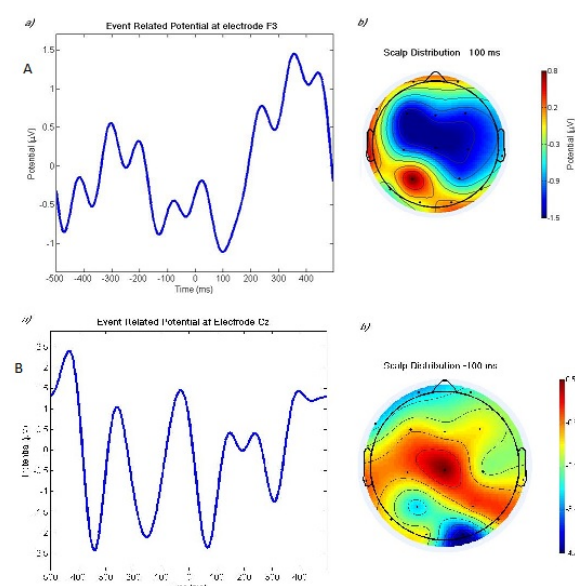

Figure 2: Event related brain potential at F3 time-locked to drum hit sounds in the non-movement (listen) condition; A) Scalp distribution of potential at 100 milliseconds post drum hit shows distribution mainly over center of head B) B: Event related brain potential time-locked to drum hit action in solo condition a) Scalp distribution of potential at 100 milliseconds prior to drum hit shows a similar distribution to Figure 2b.

Spectral analysis

For initial comparisons between conditions, we correlated spectral power from 1-50 Hz for all condition pairs for each subject, and report frequency bands of interest based on significant differences of Spearman's Rho between condition pairs. Correlations averaged across all electrodes for the listen and play conditions, revealed high correlation in theta (M=0.87, SD=0.07, mean p<0.0001) and gamma (M=0.88, SD=0.073, mean p<0.0001) frequency bands. The mu (M=0.75, SD=0.1, mean p = 0.0025) and beta (M=0.81, SD= 0.11, mean p<0.0001) bands showed an overall decrease, with the lowest mu correlations found over the sensorimotor strip **Figure 3** for example at electrode C3), and lowest beta correlations over temporal sites [See Supplementary tables for full list of correlations at each electrode]. Overall, correlations were smaller between the listen and solo conditions, which share the least amount of sensory demands and timing information. Mu frequency band showed the smallest overall correlation (M=0.6420, SD=0.14, mean p=0.0041) with smallest correlations over the sensorimotor and other midline sites. Beta (M=0.76, SD=0.12, mean p<0.0001) and theta (M=0.79, SD=0.13, mean <0.0001) both revealed decreases when compared to the listen-play correlation, with a small increase in variance. The gamma band (M=0.86, SD=0.086,

mean p<0.0001) showed little change. Correlations were strong across all frequencies for the play and solo conditions: Theta (M=0.9, SD=0.065, mean p<0.0001), mu (M=0.92, SD=0.03, mean p<0.0001), beta (M=0.93, SD = 0.04, mean p<0.0001) and gamma (M=0.95, SD=0.02, mean p<0.0001); all were consistently high across all electrodes.
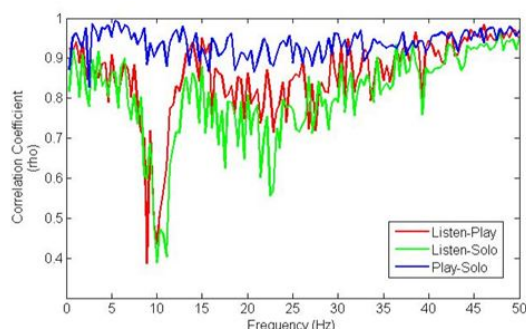

Figure 3: Correlation of task conditions at electrode C3 difference between conditions Correlations were performed at each frequency bin for spectral power between conditions.

Multivariate models of frequency band effects across conditions: Comparisons of all three tasks (within subjects) were made to examine the differences in condition per frequency band at each of the electrodes. A repeated measures ANOVA was calculated for each frequency band with factors of condition (3) and electrode (17). In the theta band, there was a main effect of condition $F_{(2,8)}=7.51$, p=0.015. As there was no baseline condition to compare bandpower and normalize within each subject for cross subject comparisons, within subject effects are reported instead. There was a main effect within subjects for condition ($F_{(2,18)}=12.29$, p<0.001), and electrode ($F_{(16,144)}=5.53$, p<0.001), and an interaction of electrode by condition ($F_{(32,288)}=2.449$, p<0.001). For the main effect of condition, across electrodes, there was a trend showing the greatest theta power for the solo condition (M=728.59, SE=8.79), followed next by play (M=723.68, SE=8.72) and least power for listening (M=711, SE=9.46). Greatest theta power was observed over central recording sites with a slight left hemisphere bias **Figure 4**. In the mu band, there was a marginally significant effect of condition ($F_{(2,8)}=3.49$, p=0.08). Within subject effects showed a significant effect of electrode ($F_{(16,144)}=2.58$, p=0.001) and an interaction between electrode and condition ($F_{(32,288)}=2.5$, p<0.001). Overall, the solo condition showed greatest amount of mu power (M=842.1, SE=9.64) followed by listen (M=836.9, SE=11.6), with the play condition showing the least (M=833.8, SE=9.9). The beta band also shows a marginally significant effect of condition ($F_{(2,8)}=3.6$, p=0.08), with the highest power seen for the solo condition (M=1679.3, SE=25.6) followed next by play (M=1666.2, SE=22.9), and then listening (M=1633.1, SE=18.8). Within subject tests show a significant interaction of condition by electrode ($F_{(32,288)}=3.23$, p=0.001), with scalp distribution showing a central to frontal bias. The gamma band also shows a significant effect of condition ($F_{(2,8)}=8.27$, p=0.011), following

the same trend as the beta band which has the largest power during solo condition (M=3023.9, SE=51.8) followed by play (M=20995.6, SE=49.4) and lastly listening (M=2915, SE=46.2). Within subjects there is a significant effect of condition ($F_{(2,18)}=14.2$, p<0.001) and an interaction of condition by electrode ($F_{(32,288)}=2.8$, p<0.001).
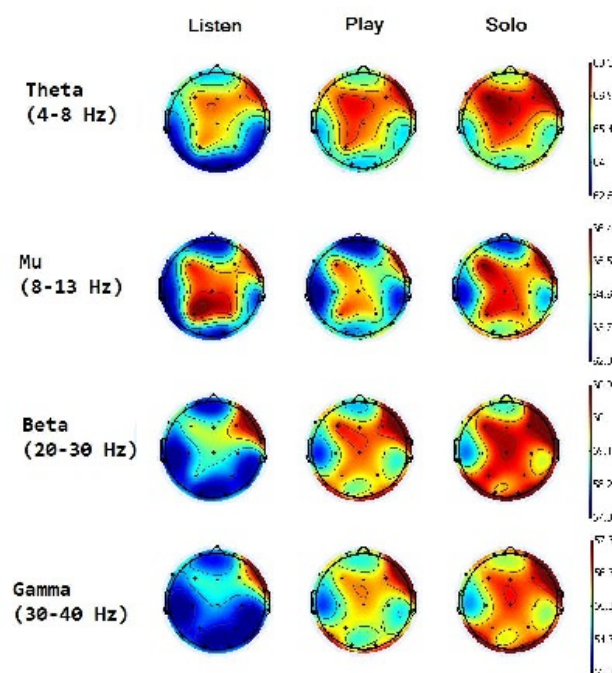

Figure 4: Scalp distribution of spectral power density across conditions. Frontal power on the right side centered beyond recording electrodes represents muscle contamination that was not removed through ICA.

Between groups comparisons: In order to make comparisons between subject group spectra it is necessary to normalize individual subject power. Since the listen condition provided the same (or at least similar) acoustical information as the two conditions where subjects drummed, this was used as a baseline for suppression calculations. As discussed in the introduction, there was no periodic pre-stimulus baseline condition. While there are likely differences in how subjects perceive the drum rhythm based on expertise, the larger domain of experience based differences is likely in playing. Suppression indices for theta, mu, beta, and gamma for a given subject were created as the log ratio of condition/baseline, in this case either play or solo condition divided by listen. Next, a two-tailed t-test compared the means of drummer and novice bandpower at each electrode, corrected for False Discovery Rate. Corroborating the conjunction analysis, the mu band showed the greatest differences between groups. In the play condition, right hemisphere mu was significantly suppressed for the drummers compared to novices at electrodes C4 (t(9)=-3.02, p=0.015) **Figure 5A** and T4 (t(9)=-2.31, p=0.05).
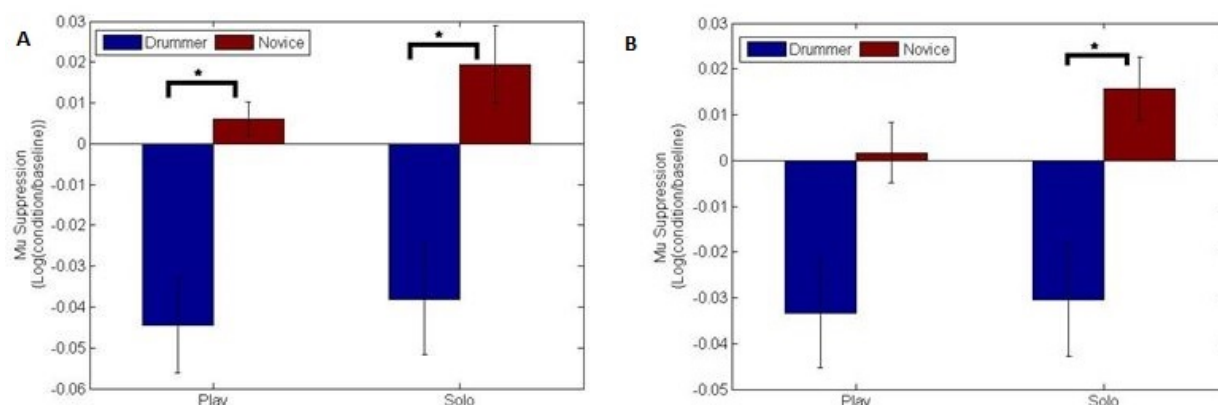
Figure 5: A) Differences in mu power suppression for drummers and novices at electrode C4; * denotes a significant difference, p<=0.05. B) Differences in mu power suppression for drummers and novices at electrode T4; * denotes a significant difference, p<=0.05.

Drummers exhibited mu suppression during movement, whereas novices showed slight enhancement when playing compared to listening **Figure 5B**. A similar effect was observed in the mu band for the solo condition as well over the central strip, with significantly greater suppression at C3 (t(9)=-2.37, p=0.04), Cz (t(9)=-2.68, p=0.03), and C4 (t(9)=-2.49, p=0.03). No significant differences between groups were observed in the theta or beta bands at any electrode. The gamma band showed a significant difference with greater suppression in drummer during the solo condition at left frontal sites F3 (t(9)=-2.3, p=0.05) and F7 (t(9)=-2.44, p=0.04).

Using the same log ratio normalized data, comparisons within group between conditions revealed no significant differences between play and solo conditions for the drummers in any frequency band or electrode. The novice group showed a significant difference in the mu band between play and solo at electrode Cz (t(10)=-2.43, p=0.04) **Figure 6A**. Greater enhancement during the solo condition (M=0.023, SD=0.016) compared to play (M=0.005, SD=0.009) is consistent with the findings above.
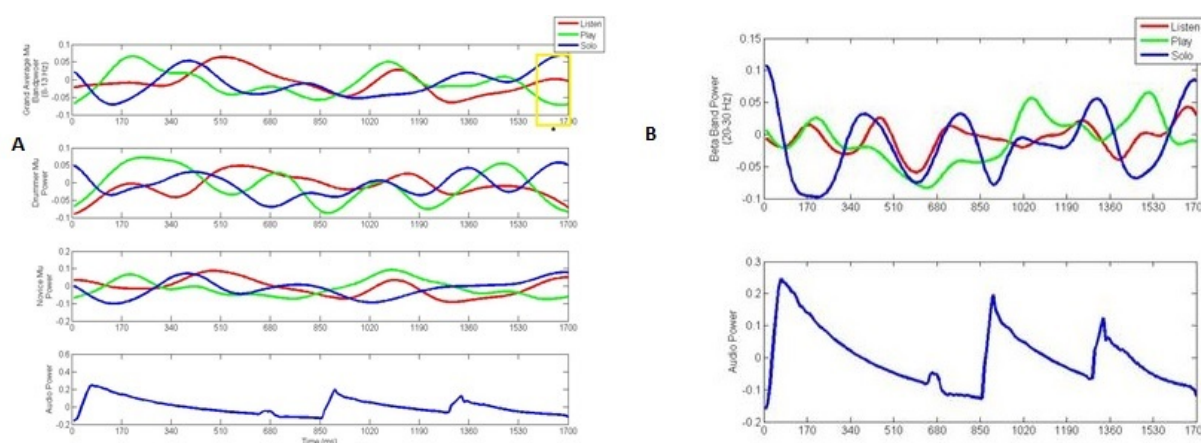

Figure 6: Differences in mu power over time for whole group, drummers, and novices. * denotes a significant difference, p<=0.05. Differences in beta power over time for whole group, drummers, and novices.

Neuro-behavioral comparisons: Pearson correlations between behavioral accuracy measures and mu and beta suppression indices for play and solo conditions did not reveal any significant correlations. To see a table of correlation coefficients, see supplemental data.
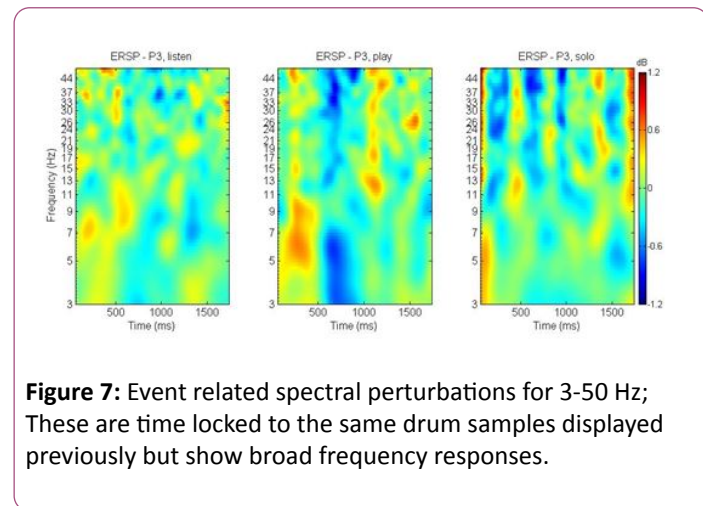
Time-frequency analysis: Visual inspection can serve to describe whether a given frequency band has peaks that correspond to those seen in the drum sample, but quantifying

the synchrony between the two is difficult. To that end, we extracted drum peaks from the envelope of the drum recording to pair against the frequency bands in a standard correlation. The envelope of drum hits shows when drum sounds occurred and the decay of the sound in the audio recording, but the decay does not necessarily correspond the sound generated by a subject in the experiment. For the mu band, electrode P3 shows the highest correlations across conditions with the drum rhythm: listen=-0.31, play=0.48, and solo=-0.43. We observed a

significant difference between conditions in the mu band at site P3, (F(2,20)=10.67, p=0.05 FDR corrected), at time 1650 ms (see supplementary results for a time-frequency statistical significance plot).

The largest correlations across all the three conditions in the beta band were observed at P3, (listen=-0.2, play=0.23, and solo=-0.4), but other sites showed correlations stronger for two of three conditions (see supplementary results). For instance, T4 showed a stronger correlation for solo (-0.4) and play (0.26) but weaker for listen (-0.07). There were no significant differences across the time window in this frequency band. Correlations in the gamma band continued the trend of a strong showing at P3 with listen =-0.2

Beta bandpower showed drum peak locking for the play condition. Prior to the drum hit a decrease in beta power is followed by a rise after the hit peaking approximately 200 ms post drum event. The solo condition showed a similar level of pre-drum hit suppression, but the latency is not as tight as play condition. The first drum hit has a negativity that overshoots the onset of the drum hit. For listen-only auditory events, a similar post drum hit positivity peaks 150-200 ms post drum hit. There are additional beta oscillations present in the listen and play condition that are out of phase with the solo condition around 170 ms and again at 1400. The change in polarity of beta **Figure 6B** and gamma oscillations, particularly for the solo condition are close in temporal proximity to the drum hits.

Figure 7: Event related spectral perturbations for 3-50 Hz; These are time locked to the same drum samples displayed previously but show broad frequency responses.

It is worth noting that many of these effects transcend the a priori defined frequency bands. Based on the broadband time-frequency plots we can see effects that transcend from the lowest frequencies to the highest frequencies displayed in **Figure 7**. Of note in the broadband display is that the mu band (8-13) is fairly attenuated compared to the other frequencies above and below it, particularly for the play and solo conditions.

Discussion

In the present study, we reported differences between experienced drummers and novice drummers in the mu band while drumming. The level of mu suppression for drummers actively drumming corresponded with previous reports of mu suppression at central electrode sites during hand action (for a review [25,26]). Contrary to expectation, novice drummers failed to suppress mu power while drumming, and showed enhancement when playing solo. While mu generally suppresses during movement, other cognitive acts may enhance mu power. Alpha power (5-12 Hz) increased over left temporal lobes when listening tasks demand a comparison of harmonic tones [27]. Holding tones in working memory is demanding, and alpha may act as an inhibitory filter to inhibit other cortical processes from interfering with working memory demands. Additionally, temporal lobe alpha (7-15 Hz) was described as participating in increased phase locking between hemisphere when subjects actively listen to pulsed sounds in frequencies that can entrain brain rhythms [28]. Increased alpha in these reports may correspond to the increased sensorimotor mu (8-13 Hz) power observed for novice drummers. Novice drummers may require additional attentional resources while playing along with a drum rhythm, and subsequently maintaining the rhythm for minutes on their own. In a previous study comparing musical perception with musical imagery, participants exhibited higher levels of alpha band (8-12 Hz) activity when imaging musical phrases rather than hearing them [29]. The current observations are also consistent with the inhibition timing hypothesis that posits increased alpha during inhibitory control over overt responses and memory recall, and these increases synchronize brain regions in a way that can inhibit other processes [30]. These findings are consistent with our observation that the highest level of mu power in novices was during the solo condition, which required the most mental effort and precise timing. Hwang et al. describe simultaneous increases in beta (18-38 Hz) and alpha (10-18 Hz) just prior to inhibition of a movement. Increased mu power in the present study may reflect an increase in vigilance, or inhibition of movement at an incorrect time.

Since this was a novel task, the behavioral analysis confirmed basic assumptions about the task, such as performance increases across trials, increased drumming stability when pacing cue was present, and better performance for experienced drummers than novices. Even though the differences were not pronounced enough to be statistically significant, the trend supports the aforementioned basic assumptions. With regard to time locked features of the EEG, this novel task elicits both motor and auditory potentials in time averaged space. The auditory ERP occurs over central sites with latency of approximately 100 ms, as reported previously [31]. There is also a distinct motor ERP that shows maximal negative deflection approximately 100 ms prior to drum hit, and exhibits the pre-motion positivity in the remaining time leading up to drum hit that is described in Deecke [32] when subjects prepare to move an arm. Much of the motor preparation literature describes preparation of finger movements, but in the drumming task subjects engage whole arm movements, and the pre-motion positivity is not as evident for simple finger flexions. While more validation studies are needed with this drumming task and comparison of different drum rhythms, it shows promise as an engaging, naturalistic behavior to test in the laboratory. One undergraduate research subject said that this was the most interesting experiment she had participated in, while another one mentioned this was the least boring.

We correlated spectra for all pairs of conditions as an initial approach to ask whether the brain rhythms engaged during drum play resembled those of listening to drum rhythms. The play and solo conditions shared high degree of correlation, consistent across all the spectra. Deviations between play-solo high correlations, and listen-play and listen-solo correlations revealed relatively large differences in mu and beta bands, likely related to task relevant motor and somatosensory processes. The relative similarity in gamma band across all conditions suggests a role in auditory processing, as this stimulus feature was present in all conditions. Gamma has been reported in musical beat processing [10, 11]. Gamma band activity has been show to vary with musical training, where trained musicians show an increased evoked potential when listening to their own instrument [33], however our results showed lower gamma power for drummers relative to novices during movement and no significant differences when just listening. Given that the gamma band is not reported to participate in event related desynchronization, the decrease in gamma in drummers may actually indicate an increased processing load in novices, however it cannot be ruled out that gamma is indexing attention with these responses. We also observed high levels of theta power across all conditions. It is possible that the drum rhythm itself could have affected the lower edge of theta power: with four drum hits over 1.7 seconds, the drum hits presented at a frequency of approximately 2.35 Hz, however the inter-stimulus-interval varied from 200 to 600 ms, which over laps with theta intervals of 250 ms at the lower edge of the band. Previous reports indicate an increase in theta power during tapping tasks [22] so this may extend to drum hits as well. Intercranial recordings in macaques likewise show a role for gamma and theta activity in auditory perception [34].

The observation that different frequency bands show significant differences across conditions is counter to the hypothesis that simulation during listening would necessitate similar power levels of activity for both listening and moving conditions. However, these might be effects that are sensitive to levels of practice or expertise, as previous studies reveal that learned associations between sounds and action sequences may form quickly Bangert et al. they may also take more than one day to form [5,21]. It is also possible that while absolute power is different between conditions, when normalized within subjects the difference may disappear. Additionally, differences in absolute power may not be the important aspect for simulation hypotheses to test. Studies of mirror neurons show that it is the temporal profile of activity of multimodal neurons that matter as opposed to absolute firing rate Kohler et al. which would translate into spectral power density in the case of EEG/MEG Caetano et al.

Neural oscillations moved in varying degrees of time locking with drum events. Qualitative description and sensorimotor band correlation with a down sampled audio clip provide preliminary estimates of musical rhythm maintenance in the cortex. Particularly in the beta and gamma bands, the play condition is indicative of a neural process linked to the drum sample in the form of a motor preceding negativity that rises after rapid drum hits as similar to that reported previously for slower rhythm intervals Caetano et al. [22]. A similar rise is observed in the listen-only condition following the drum hit. There are additional peaks of oscillatory activity that do not correspond to any particular drum hit. It is interesting to compare with reports of imagined left and right handed drumming sequences, wherein the period of event related desynchrony extended over the entire imagined play window in mu and beta bands, rather than showing patterns of event related synchrony immediate after discrete imagined movements[35]. Perhaps the somatosensory feedback of real drumming drives rebound synchrony after successive hits.

As discussed earlier, the listen and play conditions share precise timing information in that they are time locked to an external stimulus. The solo condition relies on the intrinsic timing information generated by each subject. The play condition also requires synchronizing of a pattern generator to produce the correct drum hit at the correct time, however, it has the opportunity to recalibrate every iteration of the drum sample. The asynchrony between movement tasks (solo and play) in time-frequency space, when they share high correlation in frequency space, may be explained by differences in timing mechanisms. The solo condition has greater correlation with the drum sample in the beta band than the play condition. The beta rhythm may represent endogenous timing mechanisms that correspond to the drum rhythm, whereas the play condition shows higher correlation than the solo in both theta and gamma bands. Both of these have been associated with auditory and temporal processing. Gamma includes sensitivity to things such as missing expected tones [11,36]. Additionally, these theta oscillations may have effects with envelope locked gamma band activity [34]. The lack of strong gamma or theta oscillatory activity in the solo condition may represent a lack of reliance on auditory input. Both of the movement conditions show similar correlations of mu power over time with the drum sample.

What is a good correlation for this type of task when searching for auditory signals in frequency band space? The highest coefficient reported is in the theta range and reaches approximately 0.6. Given the difficulty in directly matching a sound recording that emphasizes drawn out decay of a reverberating drum to a quickly oscillating brain rhythm, a liberal ceiling for declaring a good or strong correlation could be 0.2 and above. Even with False Discovery Rate correction, there is still a large amount of correlations that represent significant interactions. Relatively speaking, there is likely a better way to find important features in the behavior or drum rhythms to explain brain responses. To further identify motor output, the addition of EMG electrodes or infrared sensors to capture movement could help detect anticipatory movements, such as pulling the hand up before bringing it down to make contact with the drum head. Additionally, the adaptive algorithm described in the appendix for identifying epochs in the solo drumming condition could be re-purposed to seek a similar 4 drum hit peak pattern with a frequency band. The algorithm searches for a salient temporal feature, such as a long or short rest between drum hits, and then counts the number of peaks before the next feature. If it conforms to the expected pattern of hits, and the total time window falls within a preset statistical tolerance based on the past time windows, then it is counted as a good example of time locking.

Initial predictions hypothesized beta band similarity across conditions, as this follow from a simulation account of rhythmic auditory perception [8,9]. The present results showed brain rhythms in all conditions time-locked to drum hits featured in the sample. The latency between conditions is distinct, and the movement conditions contain greater suppression prior to drum hits. However, the actual results are difficult to interpret in terms of supporting a simulation account. If a similar brain process is engaged during movement and during simulation of movement without overt movement, as during a listening task, then the differences between conditions with regard to the brain process should be small. While there was no statistically significant difference in the beta or gamma bands for spectral analyses and time-frequency analyses, there was a greater than chance probability that the variance between conditions could be explained by the experimental manipulations.

While there was a favorable signal to noise ratio from the large number of trials per subject, individual differences may account for large amounts of variability, hence our use of permutation statistical tests. As drumming performance and neurophysiology measures were compared with indexes based on entire session performance, the inclusion of behavioral measures to inform selection of EEG trials could further strengthen the relationship between brain-behavioral outcomes. For instance, rejection of trials where subjects made the requisite number of hits but 'lost the beat.' Ultimately, a follow up study with more participants is required for increased statistical power, and interpretation of results as related to experience. Additionally, the training of novice drummers followed by a retest session at a later date could answer outstanding questions related to attention or memory consolidation and demands on brain rhythms such as mu, particularly since changes in mu were not observed as the immediate result of a piano learning task [37] and likely take longer than a single session to adapt.

The present findings show a plausible application of hand drumming to compare listening and movement behavior with a naturalistic task in a laboratory setting. Given preliminary differences between experienced and novice drummers, this task shows promise for studying motor learning and skill acquisition. Likewise, it may provide a useful measure to describe alterations to motor function due to disease or trauma. Variability in tapping to a beat is inversely correlated with skills such as reading ability and attention [38], and drumming may confer benefits in these domains through reduced motor timing variability. Neurophysiological differences in brain rhythms suggest differences in task demands that may indicate effort, concentration, or timing that are affected by experience level. Given the limited number of participants, a follow up with more subjects is certainly in order.

Acknowledgement

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