Alpha band activity over the sensorimotor cortex during passive music listening correlates with beat tapping performance

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Abstract

Theories of music perception argue over whether observed motor area activation during passive music listening actively contributes to perception or is the product of a distributed representation. There is a growing amount of evidence linking Alpha rhythms in the motor cortex to action inhibition and imagination during passive music listening. In this work, we examine Alpha band power modulation and its association to beat perception using a sensorimotor synchronization task and a natural music listening task with electroencephalography (EEG). We sought to find an association between Alpha band modulation over the primary motor cortex and beat tapping performance. We found that greater Alpha power correlated with worse tapping performance. These results may point to a negative association between motor inhibition and beat perception and a complementary positive association between movement imagination and beat perception and production. We address these findings in terms of the HAPEM theory proposed by Schubotz (2003). This framework suggests that motor activation reflects a predictive representation formed from audio-motor association cortices, lacking proprioceptive information which could be acquired through musical training.

Keywords: action-perception coupling; beat perception; sensorimotor synchronization; Alpha rhythms; natural music.

Introduction

Music perception presents an ideal opportunity to investigate how action and cognition are coupled in the human brain. For example, consider a drummer who strikes a drum and produces a sound. From the perspective of the audience, the sound follows the movement. However, from the drummer's perspective, the intention to produce a specific sound precedes the movement. In this intention, the drummer anticipates the sensory effects of the action, forming a sensory image that precedes the initiation of the movement. Then, the sound produced is contrasted with the sensory expectation generated, allowing the drummer to confirm or correct the prediction, depending on whether the acoustic characteristics of the sound heard are consistent with the expected ones. In the case of synchronized production or movement with music, the structural characteristics of a piece require a process of extracting temporal regularities from auditory information that can be used to guide actions accurately (Koelsch et al., 2018). A clear example of this type of process is the perception of the musical pulse, which involves detecting a regular periodic beat that structures the flow of rhythmic auditory information (Ross et al., 2016) and serves as a framework for synchronizing movement to music (Patel & Iversen, 2014).

Manning et al. (2020) asked a group of pianists and non-pianists to listen to a musical sequence and decide whether the last event of the sequence aligned with the beat or not. In half of the trials, participants listened to the sequence without moving, and in the other half, they were asked to synchronize a key press with the beat while listening to the sequence. Both pianists and non-pianists performed better in the synchronization condition compared to the passive listening condition. This result is indicative of an interaction between performing a movement associated with the stimulus and how it is perceived. Furthermore, there is evidence that motor deficits can result in difficulty perceiving the beat of a musical piece (Tranchant et al., 2021). This indicates that motor activation modulates extracting regularities and assessing timing in rhythmic stimuli.

Listening to music appears to be closely connected to movement. The desire to move with music can be so intense that it happens involuntarily (González-Sánchez et al., 2018), and moving with music can reinforce positive emotions (Janata et al., 2012). Furthermore, synchronized movement with musical events is involved in prosocial behavior when the experience is shared with others (Swarbrick et al., 2019), and it has been found that the use of music has positive effects on physical performance in sports (Terry et al., 2020) and as an intervention for gait disorders (Ghai & Ghai, 2019).

Additionally, neuroscientific evidence points to a central role of motor areas in tasks involving both unsynchronized and synchronized beat tapping with music, as well as in passive music perception in the absence of explicit movement. This evidence comes from functional magnetic resonance imaging (fMRI) studies (Chen et al., 2008; Gordon et al., 2018) and electroencephalography (EEG) studies (Li et al., 2019; Nicolaou et al., 2017). While this link is well-documented, the specific role that the motor system plays during music listening remains a topic of discussion (Maes et al., 2014; Palmer & Demos, 2022). This body of neuroscientific and behavioral research on music listening without movement suggests a central role for the motor system in passive music and rhythm perception. However, this evidence raises the question of whether motor activation is necessary for musical perception or if it is the result of a domain-general representation (Ross et al., 2016).

One of the most influential theories attempting to explain the role of motor areas in musical perception is the Action Simulation Hypothesis for Auditory Prediction (ASAP) (Patel & Iversen, 2014). According to ASAP, the perception of the pulse occurs through neural signals flowing from auditory areas to motor planning areas to provide information about the timing of auditory events. These signals influence the temporal dynamics of action planning in motor areas, and then the planning signals return to the auditory system, where they generate a prediction about the timing of the next pulse. In this framework, perceiving the pulse requires generating an action plan that simulates the periodic movements associated with the pulse, thus allowing for predictions of its sensory effects. On the other hand, Schubotz (2007) proposes an alternative framework for the causal role of simulation in predicting auditory events. According to this framework, there is a fundamental difference in the format of the simulated representation, which explains why people are able to perceptually predict events that they cannot reproduce motorically. For example, a person who listens to a musical piece repeatedly could become an expert in predicting the auditory events in that stimulus. However, this person would not be able to interpret the piece with the same level of precision because they would not be able to simulate the motor instructions and proprioceptive and interoceptive feedback from the performer of the recording. The listener only has a partial sensory representation, mostly auditory, of the performed piece. Unlike ASAP (2014), Schubotz (2007) suggests that predicting musical temporal events like the pulse would not involve generating an action plan. The representation itself would be limited to the sensory format with which the listener interacts with the piece. This contrasts with the role of motor areas postulated by ASAP, as it argues that motor activation is not explicitly related to producing an action plan but to encoding certain stimulus characteristics for which the motor cortex is specialized. This raises the question of to what extent motor areas are domain-specific and, if they are, what type of information they are encoding.

A possible answer is proposed by the Habitual Map of Pragmatic Events (HAPEM) (Schubotz, 2003). According to HAPEM, predicting sensory events is structured so that predicting a sensory property P involves motor areas associated with producing that sensory property P. For example, if the property P of the musical pulse is its temporal regularity, even in a purely auditory stimulus, it could be encoded by motor areas associated with audio-phonatory articulation or body manipulation in space, such as the hands or legs (Schubotz, 2003). In the ASAP framework, the role of the motor system could be associated with simulating movement and, therefore, motor production. This would result in a modulation of motor cortex activity on areas related to movement, which could enhance both perception and production. On the other hand, according to Schubotz (2007), the motor system could be a general-domain predictive system whose activation corresponds to encoding certain characteristics determined by stimulus properties. This would result in activation of areas associated with movement that contribute to encoding a property P but would not necessarily enhance perception and production in the same way, with this effect being modulated by the proprioceptive experience given by musical training.

Mu rhythms detected in electroencephalography (EEG) are regular oscillations that occur in the same frequency band as the Alpha rhythms, between 8-12 Hz. However, while posterior Alpha rhythms are primarily recorded over occipital areas, Mu rhythms are typically observed over sensorimotor areas. Both rhythms are associated with cortical inhibition, though through different processes (Niedermeyer, 1997). While posterior Alpha rhythms are present during the inhibition of visual processes (Foxe & Snyder, 2011), Mu rhythms are associated with inhibition in sensorimotor areas (Niedermeyer, 1997). These rhythms appear both to inhibit movement explicitly and when imagining movement during passive tasks (Pfurtscheller, 1994; 1997). For example, literature on brain-computer interfaces in which users guide the movement of virtual vehicles through imagination, shows a negative modulation of Mu rhythms during the task (Yuan & He, 2014).

Despite growing evidence linking Mu rhythms with the imagination of movement and the inhibition of action, there is limited literature exploring the presence of Mu rhythms during music listening. Li et al. (2011) showed that the presentation of an auditory stimulus associated with an action can modulate the activity of Mu rhythms after a brief session of associative learning between auditory stimuli and movements. However, while the stimuli used were auditory and could be considered musical, they lacked the hierarchical and structural characteristics of natural music. In the study by Mercadié et al. (2013), music was used to accompany an osteopathic rehabilitation treatment in two musical conditions and one silent treatment condition. In one of the musical conditions, both the patients and the therapists listened to the same music synchronously, while in the other, the music was the same but desynchronized. In this study, they found that the desynchronized music condition was accompanied by the presence of an event related desynchronization (ERD) in the Alpha band rhythms, a marker of disfluency in sensorimotor learning.

On the other hand, in the study by Wu et al. (2016), they found evidence of a negative modulation of alpha power, associated with the desynchronization of Mu rhythms, in a group of pianists presented with excerpts of melodies compared to a silent condition. In a subsequent study (Wu et al., 2017), they found functional connectivity between motor and auditory areas in pianists and non-musicians who received a brief period of musical training mapping tones to piano notes. In particular, the changes in functional connectivity were specific to stimuli with melodic content and were not present for purely rhythmic stimuli. Interestingly, the same modulatory effect on Mu rhythms was observed in pianists but not in non-musicians. This could indicate that the modulation of Mu rhythms depends on more extensive musical training, whereas functional connectivity does not. In another study, Behmer & Janzten (2011) found a negative modulation effect on Mu rhythm power upon the presentation of sheet music to pianists, demonstrating that the same effect could be produced via different sensory modalities. These results could indicate the presence of an action plan being inhibited when synchronization causes an increase in alpha power or even the imagination of movement associated with auditory stimuli, while desynchronization causes a reduction in alpha power.

These works provide evidence towards the relationship of Mu rhythm modulation, movement and music listening, but do not indicate whether this modulation is related to beat perception or tapping. An exception is the work by Ross et al., 2022, where the increase in Mu rhythms' intensity has been detected in tasks involving the pure perception of natural music compared to a silent condition. The study had four conditions. In the first condition, subjects had to remain still and silent; in the second, they had to tap a surface with their right index finger at a frequency of about 2 taps per second without music; in the third, they had to tap the floor with their right foot at a frequency of about 2 taps per second without music; and in the fourth, they had to listen to excerpts of natural music while remaining still. The finding of increased Alpha band power during the passive music listening condition compared to the other conditions is interpreted as evidence of an action plan being inhibited, since sensorimotor coupling can lead to the need to move with the pulse (Janata et al., 2012). According to the authors, this would be consistent with the ASAP framework (Patel & Iversen, 2014), where active motor planning is implicated in the pure perception of the pulse.

The study by Ross et al. (2022) is the only example of detecting Mu rhythms in the passive perception of natural music. They associate the presence of Mu rhythms with the need to move associated with the pulse. However, the study does not include a measure of the association between these rhythms and the accuracy with which the pulse is perceived or produced. Therefore, we cannot assume that the presence of Mu rhythms during passive music listening is linked to the pulse instead of another characteristic of the stimuli.

Additionally, previous studies find a negative association between the auditory or visual presentation of musical stimuli and the modulation of Mu power. Therefore, there is still ambiguity regarding the functional relationship between Mu rhythms and the perception of the musical pulse. The contradictory effects in terms of the direction of modulation could reflect different roles of Mu rhythms, with positive modulation indicating inhibition of movement and negative modulation indicating the imagination of movement. Thus, a correlation between alpha range power and beat tapping could be positive, indicating that greater inhibition is associated with improved pulse perception, or negative, indicating that less inhibition is associated with better pulse perception.

To investigate how Mu rhythms are associated with the accuracy with which the pulse is perceived and produced, we analyzed performance in a sensorimotor synchronization task and fluctuations in Alpha band power during passive music listening. Sensorimotor synchronization has been widely used to evaluate the ability to perceive and produce a pulse in the literature (Repp & Su, 2013). In this task, subjects are asked to listen to a piece of music and mark the pulse they hear. To evaluate performance in the beat tapping task, we use an entropy measure between the time intervals of each beat tapping (E-ITI). The E-ITI is a measure of variability calculated from an estimate of the probability distribution of intervals between markings (Miguel, 2022).

We expected to find a correlation between the average activation Alpha frequency rhythms over sensorimotor areas and accuracy in the pulse synchronization task. Given that previous literature was inconclusive on this point, no specific hypothesis was made regarding the direction of the association, which could have been positive (possibly indicating inhibition) or negative (possibly indicating imagination).

Methods

Dataset

A publicly available dataset (Losorelli et al., 2017) was used. The dataset comprises EEG recordings taken during a passive music listening task and a beat tapping task using excerpts from the same stimuli (without EEG recording). The dataset includes both raw EEG data and preprocessed data. For the present study, the preprocessed data were used.

Participants Twenty right-handed participants, aged between 18 and 29 years (M: 23 years, SD: 2.8; 30% female), participated in the study. All participants reported having normal hearing abilities, fluency in English, and no cognitive deficits. There were no inclusion criteria related to musical training. Seventeen participants reported having received musical training (M: 7.1 years, SD: 6.7, among those who reported training). The participants reported listening to between 3 and 35 hours of music weekly (M: 14.3 hours, SD: 10 hours). A non-probabilistic intentional sampling method was used. The study received approval from the Institutional Review Board of Stanford University, and all participants signed an informed consent form.

Stimuli Ten natural music pieces containing steady, electronically generated beats in binary meter and varying tempos in the range of 55-150 bpm were used. All pieces were between 4:30 and 5:00 minutes in length and contained lyrics in English (except for one) and are within the Western music tradition. For the EEG portion, a click track was added to the stimuli and fed into the EEG amplifier to allow precise synchronization of the stimuli with the EEG signal. For the behavioral portion, 35-second excerpts from 1:00 to 1:35 of each piece were selected, with a fade-in applied during the first 2 seconds and a fade-out during the final 2 seconds, and 1 second of silence was added between stimuli to make the transition clearer for the participants.

Instruments An ad-hoc questionnaire was administered to assess age, weekly hours of music listening, and years of musical training. Additionally, two 1–9 scales were used to measure the familiarity with each musical piece and the enjoyment participants experienced with each piece.

EEG Recording EEG data was collected with 128 channels, using the Electrical Geodesics, Inc. (EGI) GES300 system at 1 kHz. We used the preprocessed data from Losorelli et al. (2017). Preprocessing included filtering, downsampling to 125 Hz, bad electrode rejection and removal of EOG components with ICA.

Procedure The procedure began with the administration of the demographic and musical experience questionnaire. Then, EEG data collection was carried out. During this phase, no explicit reference was made to the tempo or pulse of the musical pieces. Participants were instructed to listen attentively to the songs without making any movements during the trials. The songs were presented in random order, and after each trial, participants rated the familiarity and enjoyment of the piece they had just listened to.

The EEG study was divided into two consecutive blocks to avoid fatigue effects, limit the volume of data, and allow for electrode verification. Stimuli were presented through Genelec 1030A speakers at a volume range of 73-78 dB. During the task, participants observed a fixation cross on a computer monitor placed in front of them.

After completing the EEG portion, the electrodes were removed, and the behavioral task began. In this phase, each participant listened to the 35-second excerpts of each song, after receiving instructions to "tap to the steady beat of the song as you perceive it.". To record the beat tapping responses, the iOS Tap-It application (Kim, 2012) was used, which allows for audio playback while recording tactile responses on the touchscreen of a device, with an average latency of 15 ms (standard deviation of 5 ms). In this study, an Apple iPad 2 and a set of Sony MDR-V6 headphones were used.

Data Analysis

EEG data analysis was carried out in Matlab (version R2020a). Three regions of interest (ROIs) associated with the presence of Mu rhythms in motor areas were selected based on prior literature (Debnath et al., 2018; Pfurtscheller et al., 1994; Pfurtscheller et al., 1997): right arm (electrodes 87, 93, 103, 104, 105), left arm (electrodes 30, 36, 37, 41, 42), and legs (electrodes 7, 31, 55, 80, 106).

To look for Mu rhythm modulation during passive music listening, two EEG measures were used to characterize Alpha rhythm presence: the mean power in the alpha frequency range over time (MPA) and the deviation of power in the alpha frequency range over time (DPA). The *pspectrum* function was used to obtain the spectral density for each electrode within each ROI, segmenting the signal into 1-second time windows. Alpha frequency power (8-12 Hz) was extracted for each window, and the average over frequency bins for each electrode within each time window was calculated. The average of the electrodes in each ROI was normalized by computing the quotient between each electrode and the average of all electrodes for each time window and then the mean of all time windows was calculated. To generate more robust electrophysiological measures of Alpha rhythms and reduce the number of multiple comparisons, the values of the electrophysiological metrics from each ROI were averaged.

The deviation in power (DPA) was selected for its sensitivity in detecting more extreme fluctuations in the power characteristic of Mu rhythms. We calculated DPA as the standard deviation of power for each time window in the alpha frequency range for each electrode. This dispersion was then normalized by computing the quotient between each electrode for each time window for each ROI as well as the average of the three ROIs.

The clarity measure of the musical stimuli was extracted using the *mirpulseclarity* function from MIR Toolbox version 1.8.1 (Lartillot et al., 2008). This measure represents the clarity with which the pulse of a song is perceived, a property that may relate to body-specific coding of different types of information, according to Schubotz's (2007) theory.

To evaluate the relationship of Alpha modulation with beat perception, we estimated a subjective measure of pulse clarity from the participant's tapping data as the entropy of their inter-tap intervals (E-ITI) (Miguel, 2022). This measure reflects variability in the synchronization response, where higher values indicate poorer performance.

Data analysis for the synchronization task, questionnaires, and associations between both data sets was conducted in Python (version 3.10.4). Extreme values were removed by trimming scores that were ±2 standard deviations for EEG variables, entropy, and the enjoyment and familiarity metrics (at the song and participant levels), resulting in an 11% data loss.

Given the known associations between measures of rhythmic complexity and participants' ability to perceive and produce the pulse, as well as the modulation of neural processes involved (Cossavella, Miguel & Slezak, 2023; Dean et al., 2021; Mathias et al., 2020). Pulse clarity is a measure of the intensity with which the pulse of a song is perceived, expressed as a positive value. In previous studies, this measure has been significantly associated with variability in beat tapping, indicating that lower pulse clarity values are associated with higher variability in beat tapping (Miguel et al., 2020). For the stimuli in the present study, pulse clarity ranged from .35 to .78 (M = .55, SD = 1.11), showing a lower degree of variability compared to other datasets used in the literature (Miguel et al., 2020; Mirex, 2006).

The Shapiro-Wilk test (Shapiro & Wilk, 1965) was applied to assess the normality of the distributions of EEG and E-ITI variables to determine whether parametric or non-parametric association tests would be performed. Non-parametric correlation analyses were carried out using Spearman's correlation test. First, a correlation matrix was computed for the MPA, DPA and E-ITI variables, as well as for musical training, hours of music listening, enjoyment, familiarity, tempo, and pulse clarity. Then, partial correlations (Baba et al., 2004) were performed between MPA, DPA and E-ITI for each ROI and total. The partial correlation method allows controlling for the effect of other interacting variables, particularly controlling for training, enjoyment, tempo, and pulse clarity.

To evaluate the association between fluctuations in alpha power and beat tapping performance, partial correlations were computed between MPA, DPA and E-ITI for all ROIs simultaneously. Subsequently, partial correlation analyses of the same variables were performed for each ROI independently. Partial correlation analyses were carried out using the *partial_pcorr* function, an implementation of the *pcor* function from the R *ppcor* package (Kim, 2015)

Results

The result of the Shapiro-Wilk test (Shapiro & Wilk, 1965) indicated that both MPA, DPA, and E-ITI were not normally distributed. Therefore, the correlation analyses were performed using Spearman's coefficient, and a significance threshold of $p < 0.05$ was set. The stimuli had a mean enjoyment score of 5.95, with a standard deviation of 1.97. The mean familiarity score was 1.38, with a standard deviation of 1.4. The E-ITI measure had a mean of 1.10 with a standard deviation of 0.40.

As a result of the correlation matrix analyses, a significant negative correlation was found between DPA and the enjoyment measure ($r = -.16$, $p < .05$) and a significant positive correlation was found between DPA and years of musical training ($r = .23$, $p < .01$). No significant correlations were found between EEG variables and familiarity, pulse clarity or tempo. To control for the effect of existing correlations between the variables of interest (EEG and E-ITI measures) and other variables (musical training and enjoyment), partial correlations were used (Table 1). When partial correlation was applied to control for the effect of enjoyment and musical training without segmenting by ROI, a significant positive correlation was found between MPA and the E-ITI measure ($r = .24$, $p < .001$), and between DPA and the E-ITI measure ($r = .26$, $p < .001$). Regarding each ROI, significant positive correlations were found for MPA and the E-ITI measure in the left arm ROI ($r = .17$, $p < .01$), right arm ($r = .16$, $p < .01$), and legs ($r = .17$, $p < .001$). Similarly, significant positive correlations were found between DPA and the E-ITI measure for the left arm ROI ($r = .22$, $p < .001$), right arm ($r = .23$, $p < .01$), and legs ($r = .23$, $p < .01$).

Table 1: Partial correlation between EEG measures and Entropy.

Measures	**E-ITI vs. MPA**	**E-ITI vs. DPA**
Total	.24**	.26**

Right arm	.16*	.23*
Left arm	.17*	.22**
Legs	.17**	23*

Note: The partial Spearman correlations were reported for all EEG and beat tapping variables. MPA: mean power in the alpha frequency range; DPA: dispersion of power in the alpha frequency range; E-ITI: entropy between intervals.
*p < .01, **p < .001

Conclusions

Prior research has established a close relationship between motor system activity and rhythm perception, with evidence showing that movement improves beat perception and that motor deficits can impair rhythmic processing. The Action Simulation Hypothesis for Auditory Prediction (ASAP) suggests that motor planning areas are involved in predicting the timing of auditory events, while alternative frameworks, such as HAPEM, propose that the motor system encodes sensory properties of stimuli without necessarily generating action plans. In this study, we investigated how Mu rhythms, associated with sensorimotor inhibition, are modulated during passive music listening and their relationship to the accuracy of pulse perception and production.

Using a sensorimotor synchronization task and analysis of Alpha band power during passive music listening, we aimed to clarify the functional role of Mu rhythms in rhythm perception and contribute to understanding the interplay between motor and auditory systems. We expected to find an association between alpha frequency power and beat tapping performance, though previous literature is conflicting regarding the direction of the correlation. We found a positive correlation between alpha power (mean and standard deviation) and entropy between intervals, indicating a negative performance measure. This suggests that alpha power might reflect inhibition of movement, which could decrease pulse accuracy, or that movement imagination improves pulse perception.

This suggests that the motor system, even in the absence of explicit movement, plays a role in processing temporal regularities in music. These findings align with the Action Simulation Hypothesis for Auditory Prediction (ASAP), which posits that motor planning areas are involved in predicting auditory events by simulating periodic movements. However, the observed modulation of Mu rhythms also supports alternative frameworks, such as HAPEM, which suggests that motor activation reflects a predictive representation formed from audio-motor association cortices, lacking proprioceptive information. Musical training may enhance proprioception, improving performance by providing more complete motor representations. High alpha power could inhibit pulse perception, especially for participants relying on movement to enhance performance. Notably, we found a significant positive correlation between DPA and musical training, implying a dissociation between sensory (auditory) and proprioceptive information in beat tapping.

Our results point to motor activation during passive music listening and demonstrate a novel link between alpha power, motor simulation, and sensory-motor synchronization performance. This challenges previous assumptions about the role of motor areas in passive pulse perception. The findings support Schubotz's theory, which postulates that motor activation may be sufficient for pulse perception but not for production. Since musical experience is necessary to acquire the proprioceptive information that maps perception to production, participants without proprioceptive information about that production would rely more strongly on an insufficient representation to mark the pulse accurately. Thus, this association could suggest that inhibition of movement is detrimental to pulse perception or that imagination is beneficial, with this effect potentially being mediated by musical training.

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