

École polytechnique de Louvain

Mechanisms of rhythm perception

Effect of tempo on neural and behavioral
response to musical rhythm

Author: **Hadrien COOLS**

Supervisors: **Michel VERLEYSEN , Sylvie NOZARADAN**

Readers: **Dounia MULDER, Tomas LENC**

Academic year 2021–2022

Master [120] in Biomedical Engineering

Contents

1 Introduction	12
1.1 Concepts	16
1.1.1 Pattern - cycle - sequence	16
1.1.2 Complex rhythm - simple rhythm	17
1.2 Rhythm - Beat - Meter - meter related frequencies	17
1.2.1 Beat is perceived according to the meter	19
1.2.2 The EEG response is more pronounced at meter related frequencies	20
1.2.3 Beat perception range	20
1.2.4 The brain has an endogenous ability to generate and perceive rhythm	21
1.2.5 Area involved in beat perception	21
2 State of the art	23
2.1 EEG	23
2.2 Evoked related potential (ERP), steady state evoked potential (SS-EP), Frequency tagging related potentials	24
2.2.1 Evoked related potential (ERP)	24
2.2.2 Steady state Evoked related potential (SS-EP)	25
2.2.3 Frequency tagging	26
2.3 SNR	28
2.3.1 Noise Sources	29
2.3.2 Noise measurement and quantification	30
2.3.3 Standard error measurement	31
2.3.4 Spectral based SNR	32
2.3.5 Noise reduction	33
3 Material and methods	35
3.1 Design of the experiment	35
3.1.1 Montage	35
3.2 Overview of experimental process	39
3.2.1 Neurocognitive task: listening trial	40
3.2.2 Behavioral task: tapping trial	47

3.3	Development of the procedure and legacy	50
3.4	IT and analytics architecture	52
3.4.1	Architecture of the pipeline	52
3.5	Implementation of the architecture	56
3.5.1	Downloading data	57
3.6	Pull data from source	57
3.7	Cleaning raw data	57
3.8	Extraction of data from the tapping test	58
3.9	Selecting bad channels	58
3.10	Preprocessing	58
3.10.1	Filtering and decimation	59
3.10.2	Application of the ICA	59
3.10.3	Epoching	61
3.11	Rejecting epoch	61
3.12	Transformation of data	61
3.13	Perspectives for preprocessing	62
3.14	Group level analysis	62
3.15	Tapping analysis	63
3.15.1	Time intervals between taps	64
3.15.2	Classification	66
3.15.3	Assess of the quality of tapping, error and bias	66
3.16	Time visualization	70
3.17	Frequency analysis	70
3.17.1	Overall gain	71
3.17.2	Input output analysis	71
3.17.3	Scalp distribution	71
3.17.4	Meter related frequencies	72

4 Results	74
4.1 Participants data	74
4.2 Tapping analysis	76
4.2.1 Measure inter-tap intervals	76
4.2.2 Difference in the tapping period between the 3 tempi	76
4.2.3 Representation of ITI for each tempo	77
4.2.4 Classification and error set	85
4.2.5 categorization and performance	89
4.3 Time domain visualization	89
4.4 Frequency analysis	91
4.4.1 Spectrum at frequencies of interest	91
4.4.2 Overall gain	94
4.4.3 Input - output comparison	94
4.4.4 Scalp distribution	96
4.4.5 Meter related frequencies	97
4.4.6 Z score meter related	98
4.4.7 Summary	100
5 Discussion	101
5.1 Conclusions	103
6 Annex	105
6.1 Recruitment flyer	105

List of Figures

1	Illustration of pattern cycle and sequence.	16
2	Comparison between a complex and simple rhythmic pattern.	17
3	Comparison of theoretical beat perception associated with the meter	19
4	Projection of the activity of the brain	22
5	Illustration of electro-chemical (redox) reactions at the edge of the electrode.	23
6	Evoked potential	24
7	Multiple ERP	25
8	Illustration of oddball experiment for SS-EP	26
9	Overview of frequency tagging analysis process	28
10	Listening trial.	29
11	Kernel representation of neighbors frequency filter.	33
12	SNR and subject.	34
13	Montage schematic.	36
14	Layers between brain cortical and electrodes.	37
15	Diagram of the experimental procedure.	40
16	Auditory stimulus pattern cycle.	41
17	Audio pattern.	41
18	Representation of 2 pattern cycle with the envelope.	42
19	Analytical signal of a pattern cycle and dft of a sequence.	42
20	Sequence representation.	43
21	Listening trial.	45
22	Illustration of the fixation task concept	46
23	Tapping trial.	47
24	Usual tempo tap representation.	49
25	Comparison tones-clicks signals	51
26	Sum up of the pipeline architecture.	56
27	View of ICA signals on a topography.	60
28	Usual eyes blink independent component.	60
29	Usual eyes shifting independent component	61
30	Usual tempo tap representation.	64

31	Usual tempo tap representation.	65
32	Biais precision.	67
33	Pairwise T-test P value representation	77
34	Histogram and distribution representation of ITL.	78
35	Usual tempo tap representation.	79
36	Diagram showing the distribution of tapping behavior.	80
37	Error accumulation representation.	81
38	Usual tempo tap representation	82
39	Cyclic representation of the tapping	83
40	Illustration of a good tapper for a trial.	84
41	Illustration of a bad tapper for a trial.	85
42	Histogram of classified trials	86
43	Usual tempo tap representation.	87
44	Diagram showing the distribution of tapping behaviors.	88
45	Bad tappers distribution across tapping models	89
46	All trial EEG responses in the time domain.	90
47	Pattern cycle EEG responses in the time domain.	90
48	Evoked potential compared to the input audio stimulus.	91
49	View of SNR at interest frequencies.	92
50	View of standard deviation on the spectrum.	93
51	Post hoc illustration of amplitudes across tempi.	94
52	Comparison between input audio sequence and EEG response.	95
53	Topomap representing cortical activity and standard deviation.	96
54	Selected electrode for analysis.	96
55	Spectrum harmonic with frequencies related to a 3 tapper model.	97
56	Representation of z scores between times.	99
57	Visualization post hoc tests.	100

List of Tables

1	Comparison of brain investigative methods.	38
2	Participants information.	75
3	Contingency table bad tappers across tempi.	87
4	Chi square sum up bad tappers across tempi.	87
5	Contingency table bad tappers.	89

Glossary

Bias Systematic error.. [80](#)

Frequency tagging related potentials Evoked potential after presentation of steady sequence using frequency tagging.. [1](#), [13](#), [24](#)

Intracranial EEG Intracranial electroencephalogram using invasive electrodes.. [38](#)

Mean vector length Mean vector length representing a concentration of points in a circle, the length is correlated with the concentration.. [68](#), [84](#)

Meter related frequencies Musical sequence where rhythm is distinguishable and periodic.. [12](#)

Nociceptive Activation of the pain neural pathway.. [26](#)

Pattern Arrangement of silence and impulse disposed on same interval, unit of construction of a sequence.. [14](#)

Pure tone Signal composed of an unique sinusoidal.. [40](#)

Sequence Incoming sound as stimulus, composed of a repetition of the pattern.. [13](#)–[18](#), [41](#), [102](#), [103](#)

Tempo Speed how is played the sequence.. [14](#), [101](#), [103](#)

Acronyms

ADC analog to digital converter. [44](#)

ANOVA analyse of variance. [63](#), [76](#), [94](#)

BiDs brain Imaging Data Structure. [57](#)

CMMR common mode rejection ratio. [39](#)

CMS common mode sense. [38](#)

DFT discrete Fourier transformation. [70](#)

DRL driven right leg. [38](#)

EEG electroencephalogram. [13](#)–[15](#), [31](#), [35](#), [45](#), [47](#), [74](#)

ERP svoked related potential. [1](#), [24](#), [31](#), [90](#)

FFT fast Fourier transformation. [32](#), [70](#)

FMRI functional magnetic resonance imaging. [38](#)

ICA independent component analysis. [58](#)

IONS institute of Neurosciences. [74](#)

ITI inter tapping interval. [64](#), [65](#), [76](#)

MCCA multiway canonical correlation analysis. [62](#)

PCA principal component analysis. [62](#)

RESS rhythmic entertainment source separation. [62](#)

RMS root mean square. [30](#)

ROI region of interest. [33](#), [71](#), [90](#), [96](#)

SME standard error measurement. [31](#)

SNR signal to noise ratio. [23](#), [44](#)

SPL sound pressure level. [44](#)

SS-EP steady state evoked potential. [1](#), [24](#), [25](#)

STAR sparse time artifact removal. [62](#)

Acknowledgement

Firstly i would like to thank the people who followed me, advised me and helped me on the project throughout these years.

This project represents for me an organizational challenge, allowing me to invest myself in a discipline that particularly attracts me.

I would like to thank my thesis promoters Pr. Sylvie Nozaradan and Pr. Michel Verleysen for for their advice in the scientific field of neurophysiology, their patience and for the trust they placed in me in the realization of this personal project.

I especially thank Phd. Tomas Lenc for his support at lab, his precious help and his voluntary investment throughout the year even during his resting time.

I would like to thank my family and entourage for their support throughout this challenge and through these academic years.

Finally, I would like to thank the Catholic University of Louvain la Neuve for allowing me to carry out my ambitious academic projects, and for the trust accorded and for the accorded opportunities.

Thank you,

COOLS Hadrien

Abstract

Context Humans have a natural ability to perceive beat and meter. This ability is possible due to several complex and diverse neural networks, extending from the vestibular system to cortical elaboration.

Hypothesis Perception of beat and meter can be induced by audio sequences composed of periodic pulses (as a metronome), but can also be induced complex rhythms. It seems that humans have a preferential range of perception and expression of the meter and beat. The movement is correlated to the rhythm and its expression (dance, tapping with the hands,...) and seems correlated with the perception of the meter and beat. Finally, on the EEG response, there is a link between the frequencies related to the perception of the meter and an enhancement of these same frequencies on the EEG spectrum.

Question This study is interested in the modification of features related to the EEG response and related to the perception of the meter to the presentation of an audio sequence composed of a complex rhythm when tempo is changing. The change of tempo is slight. We present here the setting up of an experiment studying rhythms, the relevance of certain parameters and metrics used in the analysis of these first results.

Material and methods The experiment is using frequency tagging, consisting of study in the frequency domain a periodic stimulus using EEG. The stimulus used is an audio stimulus composed of a complex rhythm, using 3 slight tempo variations. This constitutes the listening trial. A behavioral task assess the perception of the beat and meter by tapping on a box according to his perception of the meter. This exploits the mapping between the perception of rhythm and movement. This constitutes the tapping trial. A computer pipeline is developed to analyze these data, a focus is done on the interoperability using the latest tools for data management and for EEG data analysis.

Results This first analysis is performed on a sample of 12 participants. The results of the tapping trial show a variation of the tapping behavior, this distribution does not vary according to the tempo. The number of people who failed the task does not vary following the tempo. EEG analysis shows difference in the spectrum energy distribution between the presented auditory stimulus spectrum at the frequencies of interest derived from frequency tagging and EEG response. The Z score related to the perception of the meter are compared and does not vary across tempi.

Discussion The project is a first end-to-end approach to an experiment studying rhythm. It aims to understand the different difficulties of the development of an experiment in neuroscience. Solutions are proposed in response to difficulties and are either tested here or discussed and will be implemented in a more advanced version of the experiment. The results of the EEG response and tapping corroborate to the observations from previous studies, the detailed study of slight variation of tempo requires a larger cohort in order to be able to uncover any hypotheses and confirm certain intuitions. These preliminary results show no variation of perception across tempi neither by looking the behavioral task (tapping task) nor by analysing the Z score meter related (EEG record). This support the robustness of meter perception when the tempo stay in an human range hypothesis. There is no major shift in the perception of the beat and the meter when changing the tempo.

1 Introduction

Humans have a natural ability to perceive sounds and rhythms, and this perception of rhythm is essential for musical behaviors. Rhythms follows naturally a periodicity meter [1.2] in our countries [1], humans perceive periodic pulses that can be seen as the beat, and beats can be grouped into meters.

The perception of musical rhythms and beat is universal in the human species. The study of the rhythm perception has only been raised for a few years and studies are trying to understand in depth aspects involved in this phenomenon which seems natural for humans, the study of the rhythm remains challenging for a neuroscientist.

This link between music and humans is found through many cultures. This ability is for example illustrated during the dance activity or during the production of movement [2] during a concert, humans are very able to move following music rhythm.

Studies suggest this is due to a spontaneous ability to feel, perceive and recreate the rhythms. These studies demonstrate the link between these rhythmic frequencies at which humans move when they perceive the rhythm in music and these same frequencies found and amplified when recording neuron responses [3] 1.2.2

This phenomenon is also observed with other animals, which can be demonstrated by recording the midbrain of certain rodents. These animals suggest that a part of this phenomenon could be linked to an evolutionary phenomenon (or at least a convergent evolution) [4].

When the sound is organized in a complex way 1.1.2, when a sound does not express a prominent periodic emphasis, the behavior prove that human still manage to distinguish or "confabulate" a beat from these complex rhythmic sounds. Other species are less capable to perform this more complex task [4].

As illustration a human is still able to tap his fingers and move steadily when he is listening to audio that is not strongly periodic [5].

When looking at the spectrum of cortical activity in humans, there is a prominence (of peaks) at frequencies related to the elicited rhythm.

Using the "intracranial" recording, this phenomenon could be demonstrated at various places in the brain. But this processing is already present in the Heschel gyrus and in the nearby auditory areas 1.2.5

The research question presented below is part of the research on the brain and rhythm of the IONS laboratory (Institute of Neuroscience at UCLouvain).

The ability to sense meter periodicity is a central faculty in music perception[5]. Previous studies have shown that the ability to select pulse of the meter related frequencies (i.e. perceive distinctly a modification in a rhythmic sounds) is also found at the cerebral level. Moreover, this ability is found in animals with less evolved cortex, suggesting that the perception of Meter related frequencies (sound with a rhythmic pattern) is a low level

property of the central nervous system found during the evolution [6]. This ability is also found in some animals, even insects, that can perceive rhythmic stimuli [4].

Following exposure to Sequences expressing a prominent rhythm, the EEG response expresses an increase of the amplitudes at the frequencies related to that rhythm. For a sound (incoming Sequence) where the rhythm is more complex, (i.e. harder to distinguish) this is less obvious, but frequencies and harmonics of the frequencies corresponding to the pattern cycle period is found in EEG response.

Furthermore, certain magnitudes are enhanced, and these enhanced frequencies seem correlated with the human beat perception identified with a behavioral experiment [6].

This suggests that for a more complex sound/input (from a point of view of rhythm), the brain does not act as a system following passively the input, there is a non-linear transformation.

An emerging hypothesis is that instead there is an endogenous generation 1.2.4 of the beat (i.e. there would be an internal representation of the rhythm) [6].

The selection of meter related frequencies which are some frequencies are enhanced (even if rhythm is hard to perceive) in the EEG response suggests that this phenomenon of transformation in reaction to the input is not only based on the sub-cortical nuclei. There would also be a cortical elaboration to the auditory cortex.

Intracerebral studies, using intracerebral electroencephalogram (EEG), have shown that this phenomenon is present in primary and secondary auditory cortex, well known as Heschl's temporal gyrus (composed of the primary and associative auditory cortex, resp. area 41-42 following Brodmann's area [7]) [8] SMA and other associative part of the cortex could be involved too.

To sum up, previous studies suggest that the brain is doing a temporal selection and this ability allows the endogenous representation of a rhythm and a reaction to this internal representation of the rhythm (for example in a motor task as dancing) [6]. Note that this specific endogenous ability is (very) rarely found in other species [4].

The spontaneous endogenous generation of rhythm has been investigated. The electroencephalogram (EEG) is used to record electrical activity of neuron's population through electrodes placed on the skull.

The use of the electroencephalogram (EEG) allows to instantly capture the activity and the variation of the electrical activity of these neurons, however the method is not very accurate from a spatial point of view because the electrodes record all the electrical activity coming transversely with respect to the skull (the electronic exogenous and endogenous noise is also included) well known as "the superposition principle" [9].

The EEG response, using the electroencephalogram (EEG), under the presentation of a rhythmic stimuli reverts the form of evolved Frequency tagging related potentials, it is composed of the periodic stimulus presentation [10].

The rhythmic stimulus consists of a repeated **Pattern** of short impulses and moments of silence (fig 1).

The frequency of these evoked potentials corresponds to the frequency drawn by the envelope of the rhythmic pattern, the energy of the response at these frequencies does not correlate to the energy of the stimulus at the same frequency [10].

Moreover, the amplitude of these potentials is selectively increased at frequencies compatible with beat and meter perception (these specific frequencies are our meter related frequencies and are specific a subset of stimulus harmonics).

It can be shown by tuning the **Tempo** of the **Sequence**. If the tempo is too high, the brain cannot catch the incoming beat (it is too fast) and another rhythm is perceived.

More elements composing the pattern cycle must be integrated by the brain for rhythm perception (the brain acts as a filter slowing his relative beat perception while tempo is speeding up, to stay in the human beat perception range) [11].

These observations allow researchers to hypothesize that the brain does not simply follow the physical structure of the sound but there is indeed an elaboration.

This human beat perception range is a range of (low) frequencies qualified by rate of humanly listenable impulses and has been determined and his order is around a hertz [10].

The ability of the brain to respond to rapid rhythmic streams of stimuli is well-established. However, the internal processes that create the response to the rhythm to support perceptual organization remain largely unknown.

To sum up the hypothesis based on previous studies, the brain have an endogenous ability [12] (1.2.4) to represent the beat, even if the input **Sequence** shows a repetition of a poorly rhythmic pattern (sometimes defined as complex auditory musical rhythms or complex rhythm), the brain has the ability to enhance certain frequencies respecting a certain range of tempo [10].

The aim of the current project is to capture neural and behavioral responses to a complex input when tempo is tuned into the range receptive frequency [11].

The main research question is to explore the brain transformation to the rhythmic input by selectively enhancing behaviorally-relevant periodicities (periodicity of movement of participants while listening to the stimulus) with the influence of small tempo variation between **Sequences** (under the determined human range of beat perception) using the **electroencephalogram** (EEG). The purpose is so to investigate the EEG response to different tempi using a complex **Sequence** which doesn't induce pulse and is physically neutral in term of beat [12].

To reach this goal, the experiment is conducted in two steps, a listening trial (fig 21) and a part where the subject will have to express the rhythm perceived, this second part is named the "tapping trial" (fig 23).

During the listening trial (fig 21), the subject has to fix a point and listen to a musical **Se-**

quence

The **electroencephalogram (EEG)** response is recorded on healthy subjects while they listen to rhythmic sequences.

The recorded activity is done at low frequency between one hertz and a few hertz (from 0.5 to 6 Hz) because the frequencies involved are in the harmonics of the cycle repeating and composing the audio sequence and are in the human frequency range of beat perception **1.2.3**.

This musical sequence has some specificities (fig. **17**), it is composed of a "rhythmic" pattern which is specially designed to not express a specific frequency (fig. **1**). This complex pattern allows to test and use the hypothesis that the brain has an endogenous ability to perceive a rhythm, even when the presented rhythm is complex **12**. Perception of the meter is supposed to be a harmonic of the frequency of the pattern cycle **1.1.1**¹ according to which the pattern will be played (the rhythm is perceived in a harmonic of the cycle frequency of the pattern).

During the experiment, many sequences are played, 3 different tempi are presented (fig **52a**). There are three sequences which are structurally identical except about the tempo, there is a fast, medium and slow sequence.

This tempo variation is allowing the investigation of the influence of small variations of tempo between sequences on the response caught using the **electroencephalogram (EEG)** on the brain (the variations of the tempo played are small and remain in a range of understandable speed for the brain).

The second part of the experiment consists in a tapping trial (fig **23**), the subject will have to listen again to the sequences previously played and express the rhythm perceived by subject (or coming from endogenous representation of the rhythm) **13** by tapping on a box with a similar rhythm **14**.

This allow us to see which are the endogenous frequencies that the subject perceives and will allow us to transpose these frequencies (and their harmonics) of interest for the analysis of the **electroencephalogram (EEG)** response of the recording of the listening trial's records (the first part of the experiment).

Tapping task purpose The regularity and frequency of tapping, can be informative, if the person:

1. is understanding the task and/or,
2. is able to find a rhythm adapted to the **Sequence** heard and to stay there.

¹The frequency corresponding to the period of the pattern, consisting of a composition of 12 elements.

1.1 Concepts

1.1.1 Pattern - cycle - sequence

Pattern The pattern is the cornerstone of the experiment, it will be an addition of elements of sound and silence composing a pattern. In the experiment, the pattern is composed by 12 elements. The agency of sound and silence is chosen to generate a complex **Sequence**, so the sequence is designed to minimize the beat (and the meter) perception in an exogenous way (the experiment is interested by the *endogenous* beat perception).

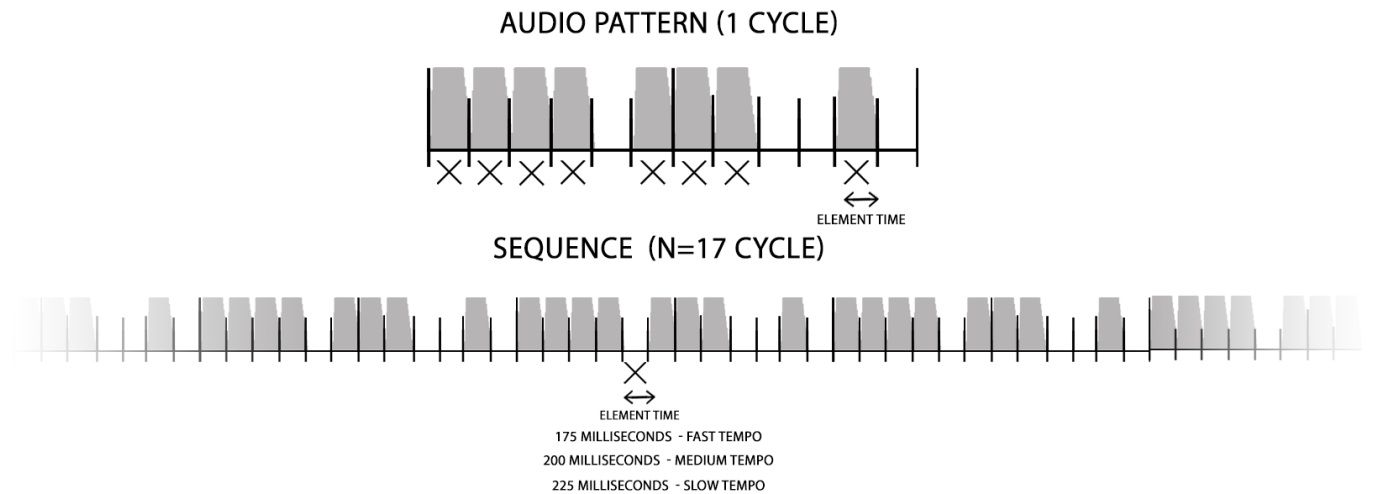


Figure 1: Top: a cycle designed via a pattern composed of elements of sound and silence, there are 12 elements in a pattern. Sounds are square envelope signals composed of pure tone signal at 200Hz. The arrangement of this pattern does not induce beat perception while listening. Bottom: succession of cycle creating a sequence. In the experiment 17 cycles are composing the trial.

The shape of the sound element can vary, for example square envelope signal (used in this project) or click signal². The time between elements played has a constant duration, by changing this duration, it is possible to modify the tempo. If each element has a short time, the tempo is high. And if each element is created with a long duration, the tempo becomes slower.

Cycle The cycle could be represented as the effective implementation of the pattern, so a cycle is equal to the pattern. This term is used to emphasize the fact that the pattern is repeated during the frequency tagging trial.

²Implementation of a Dirac impulse

Sequence The sequence is the complete repetition of these pattern cycles, so a linear and equally aggregation of cycles. In this experiment, there are 17 cycles so 17 repetitions of the pattern for each tempo.

This sequence is analyzed in the frequency domain in the furthers steps (3.2.1).

1.1.2 Complex rhythm - simple rhythm

A simple rhythmic **Sequence** expresses a marked periodicity in a beat induction point of view as a simple metronomic pulses (15) (succession of sound event disposed in a very periodic way) fig. 2. Simple rhythmic sequence expresses prominent peak at low frequency in his spectrum .

A complex sequence expresses less prominent magnitudes peak at low frequencies; the power is sparser at these frequencies.

So, the complex sequence express less the beat in the rhythm (16) .

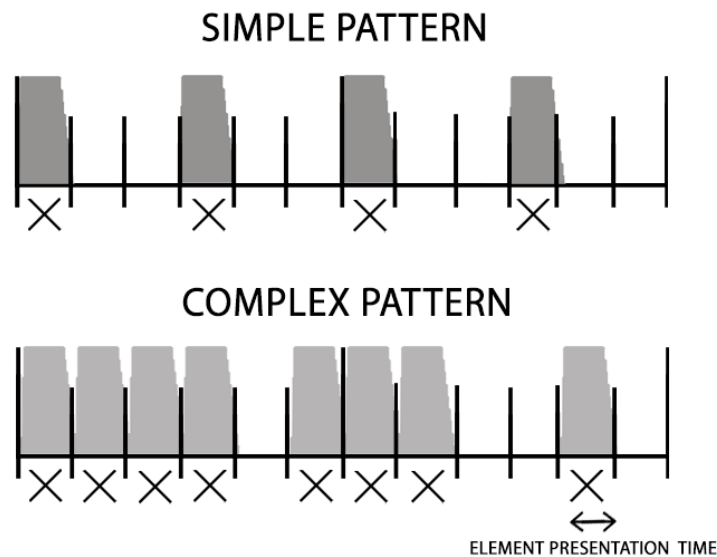


Figure 2: Comparison between simple and complex pattern. Above the simple rhythmic pattern has prominent periodicity during the pattern cycle, this elicits a strong beat detection by a listener. The complex pattern expresses the beat with less prominence, or not at all due to the weak periodicity disposition of elements composing the pattern.

1.2 Rhythm - Beat - Meter - meter related frequencies

These elements represent temporal aspects of the music.

Rhythm The rhythm can be characterized by some features, rhythmic pattern, meter, tempo and timing. A rhythmic pattern is a repetition and arrangement of events in time (3.2.1) that can be arranged in a discrete way. It can be aggregated into a rhythmic sequence (the rhythmic signal) and is a linear addition of the rhythmic pattern [17].

The rhythmic signal can be perceived with a metric structure by a listener, this metric perception is mapped on a regular pulse (the beat) or an organization of two or more levels of beat.

Beat In a rhythmic Sequence, the beat is the perception of a regularity, in the form of recurrent event.

Beat perception is therefore the sensation of a periodic pulse when listening to music or rhythmic sequence [18].

Meter The beat is a regularity perceived in rhythm. A grouping of beats forms a higher level regularity called a meter, so the meter is a hierarchical framework linked with the beat. The links between the meter and the beat are generally made in the form of an integer ratio. The meter is a dial element in a rhythm.

The meter, is a construction in structured elements (and often regular, metric) representing the understanding and interpretation of a rhythm.

Some of this mental construction ability seems to be influenced by our culture and our experiment [19]. In addition, the interpretation of the meter is not identical among people for the same music and conversely, there is a many to many relationship between the rhythmic input and the perception of the meter (1.2.1) [20] [1].

For example, for a rhythmic pattern of 12 elements, it would be possible to obtain a meter composed of 6 elements with a beat perception composed of 3 elements 6:3, therefore 2 beats per meter fig. 3.

Alternatively, it is possible to have 3 meters of 4 elements with two beats per meter of two 4:2 elements or two meters composed of beats composed of 6, so 6:2 elements fig. 3.

METER AND BEAT PATTERN OVER 1 CYCLE

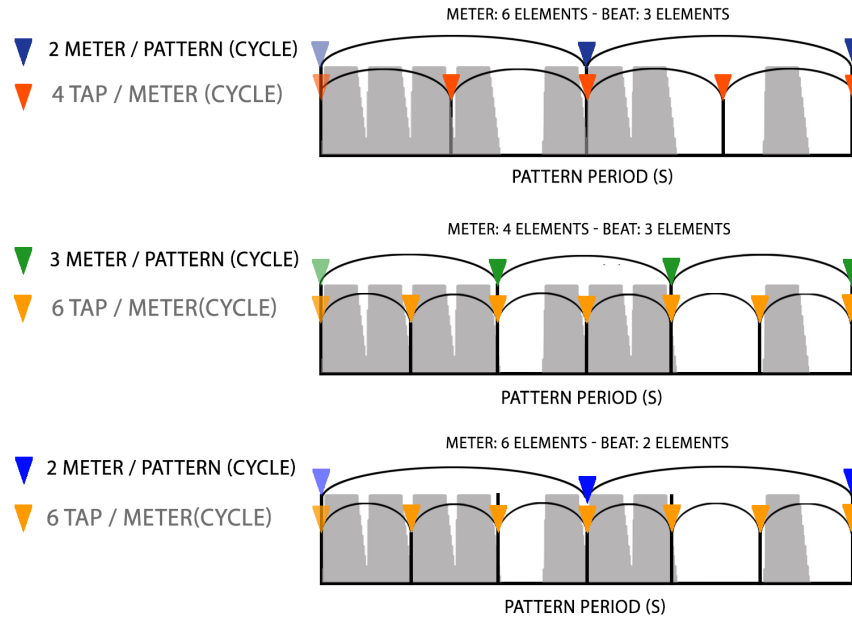


Figure 3: Comparison of theoretical beat perception associated with the meter, considering the pattern composed of 12 elements, there are multiple ways to subdivide this pattern in regular pieces. Top the pattern is subdivided by 2 meters, and 2 beats are perceived in this meter. Middle. Another possible model, is the cycle divided by 3 meters composed of 2 beats. Bottom, the cycle is subdivided into 2 meters composed of 3 beats.

Tempo The tempo refers to the impression of the speed of the sound, from a cognitive point of view, it is the speed at which the beat is played.

1.2.1 Beat is perceived according to the meter

The perception of the rhythm is done according to an interval corresponding to an integer ratio in the period of presentation of the stimulus [21] as a harmonic or a sub-harmonic. These harmonics are based on the meter of the sound played and the perceived beat is related to the most prominent harmonics selection.

The perception of the beat in relation to a meter is not done systematically in the same way, it is rather a many-to-many mapping [15], different meters can be heard with the same rhythm and the same meter can be heard with a different rhythm [1].

In motion production this is usually done at the perceived beat level because the beat is the most explicit feature when listening to audio [22].

1.2.2 The EEG response is more pronounced at meter related frequencies

The generation of the rhythm can be done spontaneously and is done by the selective activation of certain neuronal population at meter related frequencies.

The investigating is done using the EEG combined to the frequency tagging, looking at the spectral domain.

During a rhythmic process, the analysis of the EEG response shows that the frequencies corresponding to the meters related frequencies are enhanced [15], there are frequencies at which the human subject would perceive and move in rhythm following a pulse, are more pronounced at these frequencies and harmonics [11].

Even when the energy of the acoustic stimulus is not prominent at these frequencies, there is still an enhancement at these meters related frequencies [15].

The brain therefore does not completely follow the energy dispatching on the spectrum of the audio input, there is a non linear transformation performed by the involved neurons networks [23], this transformation selectively increases frequencies to meters related frequency supports the hypothesis that the brain can spontaneously recreate a beat even where there is none [15] (1.2.4).

1.2.3 Beat perception range

If the beat rhythm is sometimes perceived as a harmonic and sometimes perceived as a subharmonic of the meter of the sound played, at the level of the beat it is because the brain has a range of preferential perception of rhythms to which the perception of a stimulus can resonate optimally [24] [25] [11].

People have a meter perception preference with a period around 600 milliseconds, approximately 100 beats per minute, this beat and this perception can vary [26].

This period is according to previous studies [10] that have shown that when a trial was composed by 2.4 seconds cycles , the beat period is generally around 1.25 Hz, so 3 beats per cycle.

The participants tend to perceive the rhythm according to a grouping of the elements constituting the pattern (12 constituent elements are used for this kind of experiments) fig. 1, this is another way of quantifying the period of perception of the beat, it correspond to a harmonic of the frequency at which the pattern cycles.

The period of the pattern around 2.4 seconds seems to induce a perception of the beat with a preferential grouping of 4 elements of the pattern cycle so the participants perceive 3 beats per meter [10]. The experiment is exploring if there is a modification in this trend according to a change of tempo remaining in the range of perception of rhythms (around 1-2 Hz) [11] [27] (1.2.3).

By doubling the speed of this period, some participants tap at 2.5 Hz but a significant number keep tapping at 1.25 Hz and at frequencies lower than 2.5 Hz, which could suggest the integrative behavior of the brain and neural mechanisms for perception. endogenous beat. If the cycle is too fast (too short), the neural mechanisms could perceive two cycles as one

(aggregating) to better correspond to a natural perception of the rhythm, hence the integrating behavior (if the period is smaller than the minimum ability of integration of the brain to perceive a rhythm, this one will continue the integration until integrating several periods before expressing the perception of a beat).

An experiment conducted going up to 3 times the base speed of the tempo, this time there are an even more impressive grouping and people don't follow the high of speed with the tapping.

1.2.4 The brain has an endogenous ability to generate and perceive rhythm

Previous studies compare simple rhythms to complex rhythms [10] [22], simple rhythms physically express pronounced pulse, while complex rhythms express less pulsing, due to a difference in the design of the rhythmic pattern (1.1.2).

The beat and meter is therefore more complicated to detect in a complex rhythm, however [10] humans were quite capable of detecting a beat and synchronizing themselves with it where a lot of mammals were not. This is leading the internal representation of the rhythm hypothesis [22], the human brain could be able to recreate endogenously a rhythm and a beat and meter to be able to perceive beat and meter in complex sequence.

1.2.5 Area involved in beat perception

Areas of the brain involved in audio signal processing and endogenous rhythm perception are numerous and their exact implications in the process are unclear. Areas involved are the gyrus of Heschl [6], the primary auditory cortex and the temporal planum. The perception of rhythm already occurs early in the cortical elaboration but there seems to be linked with other areas of the brain, the parietal cortex and the dorsal pathway [28] the supplementary motor area (SMA)[29], the basal nuclei (the complex of striatum) [29] as well as the cerebellum [30]. Other structures such as the inferior colliculus [6] seem important for perception and synchronization as well.

Many of the areas mentioned above have also a major role in the production or regulation of movement, this could explaining the strong link between rhythm and movement [4].

The cortical zones are defining a region of interest during the spatial analyzes of the signals recorded during the experiment fig. 4.

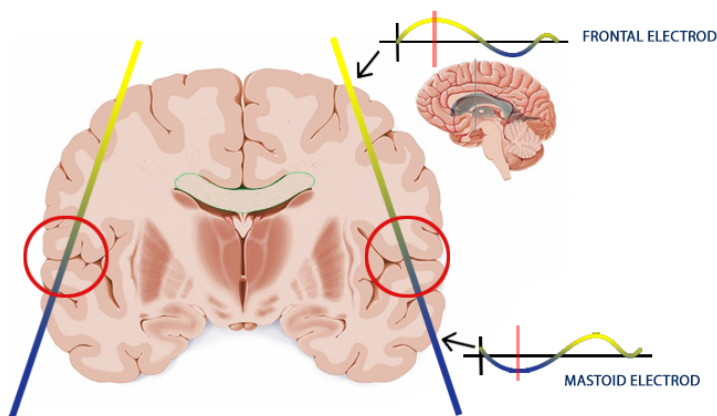
DEPOLARIZATION ELLICITED BY
MASS NEURONAL ACTIVITY

Figure 4: Projection of cortical activity induced by listening trial.

It must be kept in mind that the brain is not spherical and the part of the temporal cortex in charge of audio analysis is located in the lower lip of the valley of Sylvius fig. [4], the electrical potential is therefore projecting perpendicularly to this one, therefore in the mastoid and frontal/prefrontal areas are expressing activity on the surface of the skull [9] [31] [4].

2 State of the art

2.1 EEG

Electrodes There are different types of electrodes, there are external electrodes in contact with the skin (non-invasive), electrodes mounted on needles (invasive), electrodes in the form of layer (post cards) which are placed on the surface of the brain and intracerebral electrodes.

The principle remains the same, a displacement of ions in biological tissues, inducing a displacement of electrons which transit by the electrodes. The transduction is ensured by a redox reaction between the electrode and the gel in contact with the skin.

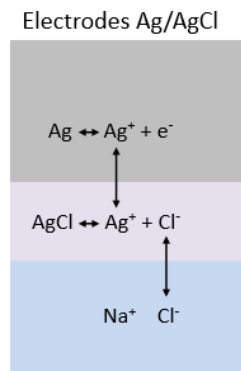


Figure 5: Illustration of electro-chemical (redox) reactions at the edge of the electrode.

The electrode catches the signal through different interfaces having distinct resistive properties, in the end the impedance depends on the

- Contact surface between the electrodes.
- The frequency, (increases the impedance by a factor $j\omega$).
- The temperature favoring the chemical reactions and the ion flow but changing electronics properties as resistor values.

Limiting the impedance is important to limit the attenuation of the bioelectrical signals, and to maximize the signal to noise ratio (SNR) [9] (fig. 10).

For this, with surface electrodes, it is possible to increase the surface of these electrodes, which reduces the impedance, but also more noise.

The choice is made to use wet electrode allowing gel to be added interfacing between the

electrode and the surface of the skull, improving conduction and greatly reducing impedance. This also erases the anatomical irregularities of the skull that could limit contact. This kind of electrodes are called "wet electrodes".

The advantage is that there is no erosion at the level of the anode as for the other electrodes due to redox reactions, because the AgCl layer is supplied with Cl^- ions by the gel (composed of $\text{Na}^+ \text{Cl}^-$) and on the other side in Ag^+ cation by the electrode, releasing an electron (therefore inducing a potential difference) to supply an Ag^+ to the AgCl layer [32].

The recent electrodes directly embed an amplification stage at the electrode level, to amplify the signal before any potential external contamination.

2.2 **evoked related potential (ERP), steady state evoked potential (SS-EP), Frequency tagging related potentials**

2.2.1 Evoked related potential (ERP)

The evoked potential is the reaction of the cerebral response following an elicited stimulus.

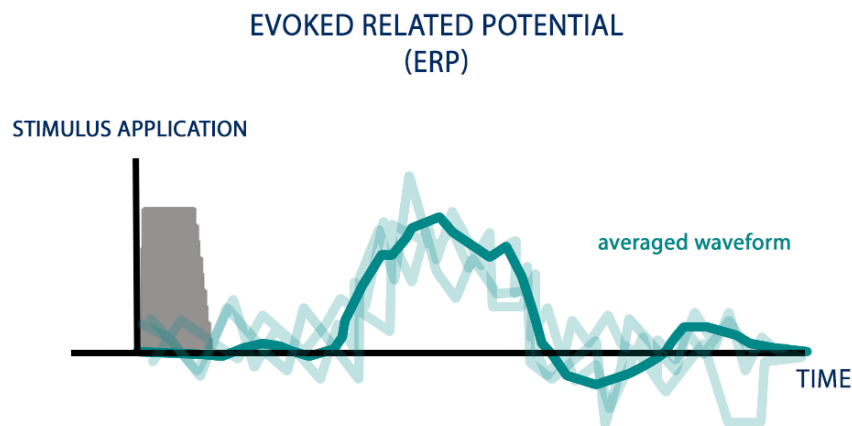


Figure 6: Evoked Potential recorded on the EEG after the presentation of a stimulus.

These deflections, that occur at low rates, produce a transient potential change [33]. These deflections are a summation of depolarization and polarization, reflecting the brain processes responding to a stimulus.

One of the bases is that the ERP arrives in reaction to a stimulus, so there is causality between stimulus and response.

In addition, there is a lag between the moment when the stimulus is presented and when the brain reacts to this stimulus. This time is the transfer time and processing time of the neurons.

An immediate reaction to a stimulus without lag is therefore an indication of a potential problem.

The ERP are characterized by peaks that can be classified according to the stimulus and these peaks appear in a time range (a window), for example an "N300" is a negative peak arriving in a window around 300 milliseconds after application of the stimulus

The stimuli are varied and can be applied to all nonsense / to each place where there is reception of nervous information [9] .

The advantages of this technique are that it can be used on the EEG, which is non-invasive and inexpensive to maintain.

Another advantage is to capture only the signals which are phase locked, as a lot of noise is randomly distributed, by averaging several ERPs, the stochastic processes (which make up a large part of the noise) are eliminated, allowing a gain in the signal to noise ratio depending (of the square) on the number of recorded ERPs fig. 8.

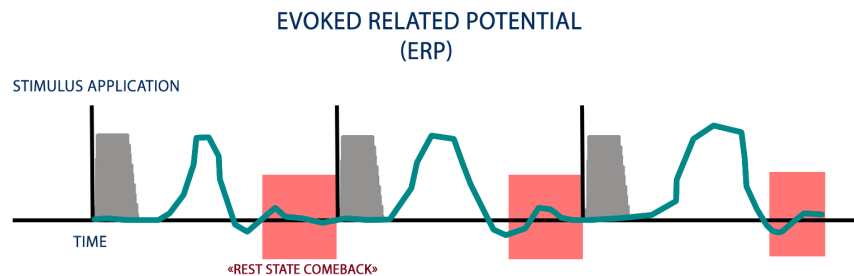


Figure 7: Stimulus can be repeated a couple of times to increase the signal to SNR, only phase locked signal is caught. The condition is to ensure a comeback to a resting state, to avoid an overlap between two successive ERP.

The ERPs obtained using EEG has a very good temporal resolution [9], whose resolution (of the order of a millisecond) makes it possible to detect whether the nerve conduction between the point of application of the stimulus and the cortical processing is damaged. The ERPs are used in the field of research but also in a certain number of applications in the medical field (research of depression, stroke, sclerosis, dementia, Parkinson, ...) to quantify specific reactions reflecting damaged or undamaged brain mechanisms.

2.2.2 Steady state Evoked related potential (SS-EP)

It is an evolution of the standard ERP (2.2), the stimulus are periodic.

The purpose of steady state evoked potential (SS-EP) is to study low level features. A periodic stimulus is presented in an experimental condition and another stimulus at another frequency rate is presented in another condition.

By studying the spectrum of the EEG response, it is possible to study neuronal mechanisms

by looking at the magnitude of these frequencies.

A simple example illustrated in fig. 8 represents an attention study, where two oscillating stimuli are on a screen. The stimuli are spatially separated and oscillate at different rates. When the participant focuses on a stimulus, his EEG response expresses a prominent magnitude at this stimulus frequency rate. When the participant is looking at the second stimulus, his EEG expresses a prominent peak at the second stimulus frequency.

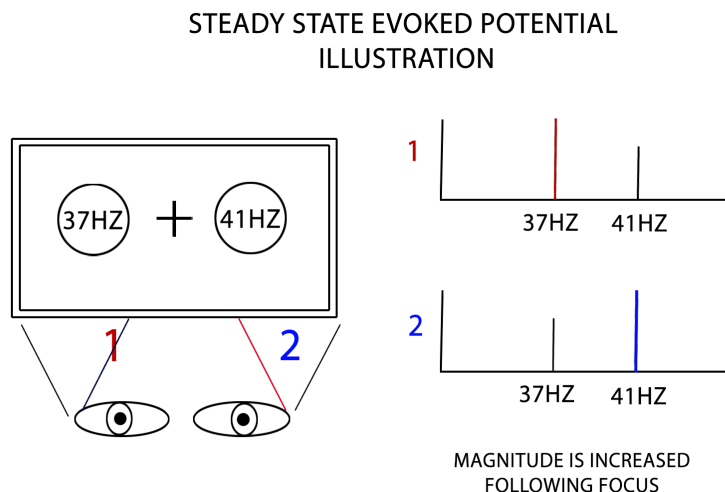


Figure 8: This experiment illustrates the principle of steady state evoked potential. The attention on the first (resp. second) stimulus is modulating the magnitude in EEG response frequencies at 37Hz (resp. 41 Hz).

A critic of SS-EP studies is a confusion and an overuse of the term SS-EP, a lot of "SS-EP" studies can be seen as a linear addition of ERP [34].

2.2.3 Frequency tagging

The principle is based on the presentation of a stimulus repeating itself with a constant period, by analyzing the spectral response of the brain (the simplest is with an acquisition using the EEG) via a Fourier transformation, it is possible to find a peak (a predominant magnitude) at the presentation frequency F (being equal to $1/T$, T is the period of presentation of the stimulus).

It is the direct measurement of the neural representation of the metric pulse, the beat in the presented application.

The stimulations and the methods of signal acquisition may vary. The stimuli can be **No-ciceptive**, vibratory, visual, or auditory (the list is not exhaustive), the acquisition methods are also multiple.

For the experiment discussed here, the stimuli modalities are auditory, because the study concerns an internal representation of the rhythm and its variation according to the tempo. The recording method is done via external surface EEG, which is the least invasive, the most exhaustive and the most temporally accurate acquisition method. This gives a lot of spatio-temporal information and can give a lot of information about the nature of stimulus processing.

However, other methods (more opportunistic) make use of intracranial electrodes which can also provide valuable information, and methods based on functional nuclear magnetic resonance (or magnetic resonance imaging) can also provide useful information on the potential localization of neural circuits studied.

- The first advantage of this method is due to the link between the stimulus and the cortical response which makes it possible to identify and serves as a starting point, as a tag in the analysis of periodic stimulations. This makes it a suitable method for studying brain processes in response to certain external stimuli.
- A second advantage is the objectivity and sensitivity of the technique, leading to a native gain of SNR.
- Frequency tagging experiments are free from assumptions such as a one-to-one mapping [1] for the representation of rhythm unlike behavioral tapping task (1) .

The frequency tagging useful to study high level mechanisms in the brain while the low level is analyzed using SS-EP.

The presented experiment, in the continuity of the experiments concerting the rhythm, would aim the validation and the visualization of a processing of this stimulus by the EEG response, but also allows to study which frequencies are enhanced [23] and which cortical areas are activated during the presentation of the stimulus [31] to understand higher level processes such as an endogenous ability to synchronize to the meter beat in humans [12] (1.2.4).

FREQUENCY TAGGING SCHEME

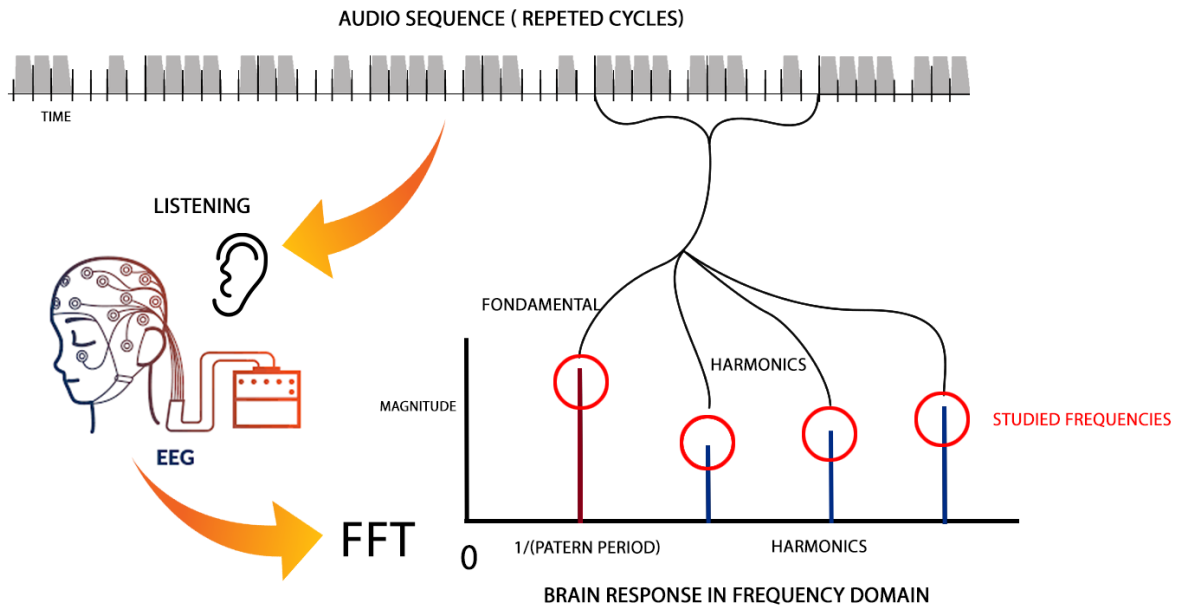


Figure 9: Periodic stimulus is applied, by looking the spectra of the EEG response, peak appear at fundamental and harmonics of this period. The study of the distribution of the energy at these frequencies bring information of how is perceived the stimulus.

The analysis of the results is done in the frequency domain, where the harmonics and fundamental of the presented stimulus are easily visible [35].

This analysis focuses on the amplitude at these frequencies, it is possible that certain harmonics have more interest, and it is therefore interesting to look at how the energy is distributed at these harmonics.

It is also important to note that the emphasis at some harmonics is not constant and depends on the stimulus, and that the brain does not operate as a "simple" passive physical system. Generated at the fundamental frequency or at a peak of smaller amplitude, other harmonics can also be very weak or amplified.

2.3 SNR

To quantify the quality of the acquired data and to be able to have an objective point of view on this quality, the concept of signal to noise ratio (SNR) needs to be implemented.

A lot of perturbations exist in the signal quality measurement metrics, however certain criteria seem important for this criterion to be interesting:

- The measurement must be made on each participant and independently of the others.

- The metric should reflect the impact noise and disturbance has on the signal and how much it might interfere with future statistical analyzes.
- The metric must be able to represent the precision through score, precision is seen in this case as the degree of repeatability that the measure has or does not have.

The concept is quite simple it matters to find the ratio between the noise and the useful signal in a measured signal. However, this definition suffers from the lack of information during experiments other than simulations, because if it is easy to know the useful signal in a simulation, it is however impossible to know it in detail for a measurement in humans by example fig. 10



Figure 10: Listening trial (1): Illustration of source noise, added to the useful signal in an additional way. Noise can be too added in further step as during recording session induced by material, or noise induced by a not well suited preprocessing.

One possibility is to compare the powers of the signal at a frequency considered as the useful signal with respect to the power of the signal outside these frequencies and these harmonics considered as noise.

It is possible to apply this measurement to several places in the data processing chain, to measure this SNRo: the SNR at the output and the SNRc: the SNR at the output of the signal processing model.

It is possible to characterize the evolution of the SNR through this processing chain and to evaluate its characteristic. We can report this with a "merit factor" = $\frac{SNR_o}{SNR_c}$ (which is the gain of SNR between two steps).

2.3.1 Noise Sources

Noise is inherent in experiments using EEG recordings (2.1) because the signal is acquired as a potential difference caused by neurons across several layers of biological tissue. Moreover, there are innumerable sources of electrical potential disturbances in the environment and the acquired signal is extremely weak.

At the level of the design, at the level of the environment, the experiment and at the level of the preprocessing.

These artifacts are usually found [36] [9]:

- Induced electrical activity from the recording environment, power line noise, environment variation (noise, vibrations), electromagnetic field noise (UV tube, elevator, cell phones, computer, screens, transformers, ...) sensor malfunctioning due to technical problem or poor skin conduction, electromagnetic interference from stim generator (headphone in this experiment).
- Biological artifacts, skin potentials; periodic QRS caused by heart activity, step shaped depolarization due to the eye's movement, short peak deflections due to the blinking movement
- Movement artifacts, EEG signals that are not phase-locked to the time-locking point (e.g., alpha-band EEG oscillations)
- Trial-to-trial variation in the amplitudes or latencies of the underlying ERP component
- Perturbation induced by preprocessing itself, induced by filter ringing, bad filter design, too strict component rejection using spatial filter and projections.

2.3.2 Noise measurement and quantification

Intuitive ways based on the literal definition of comparing the signal with respect to noise exist and propose for example to compare the **root mean square (RMS)** value of the prestimulus voltage with the post-stimulus post-voltage value [37] but the problem is that we do not compare with noise coming from the experiment itself, moreover if the signals are in the form of ERP, on the one hand we capture a signal phase locked, and on the other hand, the prestimulus is not phase locked (it is supposed to be strongly causal with respect to the stimulation, even if there could be an anticipation phenomenon) [22].

The problem with selecting and qualifying as noise the signal outside the time range of the trial is that for the experiment the noise also includes all brain processes unrelated to the applied stimulus (and having a multiple value of this one).

The brain can have phase lock responses which does not interest us, considered from an experimental point of view as noise but which activates when a stimulus is presented³.

³This is one of the alternative hypotheses to the change in tempo and the frequencies evoked by these, if these frequencies do not vary according to the tempo and the period of presentation of the stimulus, it is possible that these frequencies are just stereotyped brain activation and could disprove some hypotheses)

2.3.3 Standard error measurement

Another intuitive way to quantify the noise and the quality of a signal in a process that we want to be stable over time is to base ourselves on the variance.

One of the methods proposed and easily applicable and intended to be universal is based on measurements of the variance, which reflects the variations in relation to the mean, the truth quantifying the quality of the data, ie. the precision.

For example, if the experiment focuses on the response to a stimulus, it is possible to look at this variance between different trials.

This method is **standard error measurement (SME)** [38] and is intended to be a reflection or an alternative to the SNR measurement insofar as we do not really know the "noiseless" signal "even if one could imagine comparing it to the modeling of what one thinks to be the ideal signal (which can only be done a posteriori because this signal contains the decisive information for the results of the search, therefore contains information by definition unknown...). The estimation of the SME is done via this expression, where the \hat{SD} is the standard error of the measured feature and N is the number of tests carried out:

$$SME = \frac{\hat{SD}}{\sqrt{N}}$$

In **electroencephalogram (EEG)** using **evoked related potential (ERP)**, the most effective method to increase SNR is to repeat the experiment and average signals between epoch, however this is not infallible, and it does not remove systematic error and other artifacts, however it removes anything that does not. It is not phase locked, but our signals of interest are very often in phase lock with the stimulus, this also makes it possible to greatly reduce the variance of this signal in phase lock.

Another advantage is the versatility of the measurement, it is possible to measure each aspect of our signal having a variability and an average between the trials. However, certain features of the signal are more or less adapted to the representation of the intrinsic quality of this one..

The interpretation of the measurement is seen as the variability induced by the sum of the possible artefacts (2.3.1) increasing this inaccuracy (1.2).

Another utility of this SME is to detect potential trials considered as outliers and can therefore serve as a heuristic for a trial rejection.

Generally, increasing the number of trials should reduce this SME, it is possible that the trial has insufficient quality to have a positive impact on this variance. The inclusion of the measurement increase the noise.

However, the experiment is presenting steady repetition of stimulus, frequential techniques of SNR measurement seems therefore more suited.

2.3.4 Spectral based SNR

Another method measures the SNR on the frequency domain, because the stimulus is presented in a steadily repetitive way [39].

Through the use of frequency tagging, the spectrum show magnitude peaks at stimulus presentation frequency and harmonics [35].

The SNR is computed from the spectrum by taking the magnitude at these frequencies and making the ratio with the average magnitude of the neighboring frequencies. This procedure has two advantages.

The first is (depending on the chosen parameters) to remove the frequency hold, therefore to normalize the spectrum and to remove the power drop component at $1/f$.

Non-narrow band power modulations tend to fade out in the same way that normalization does.

The procedure is done in 3 steps:

- The first step is to calculate the spectral density, using the fast Fourier transformation (FFT) from the time signal. This allows to see the steady state processes of the stimulus and the potential response,
- The calculation of the SNR spectrum can be done on the whole graph by using a special kernel making the relationship between the centered frequency, ignoring the frequencies directly adjacent to this centered frequency (to avoid taking frequencies associated with the frequency of interest varying slightly on the spectrum) and dividing by the mean of the magnitude of N neighbors.

This calculation of the SNR spectrum in a parametric way uses two parameters which is the number of neighbors to be ignored and the number of neighbors taken in account during the average to calculate the noise.

NEAR NEIGHBORS MEAN FREQUENCY REMOVAL KERNEL

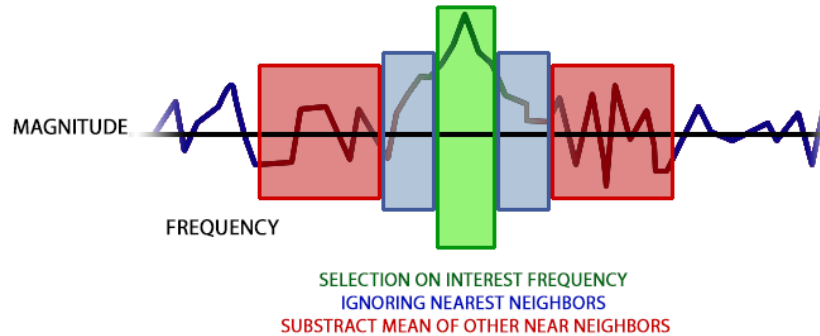


Figure 11: The kernel is broken down into 3 parts, in green, the central part corresponds to the frequency of interest, this signal is seen as useful. Blue, it is the close neighbors, which are ignored during the analysis, these close frequencies can still have an influence of the frequency of interest due to approximation during the discretization and the spreading of the signal of interest. Red are the more distant neighbors, an average of these distant neighbors is done, the average is considered as the average magnitude of the noise with respect to the frequency of interest. A magnitude ratio between the magnitude at the frequency of interest (green) and the mean magnitude of the far neighbors (red) allows an estimation of the SNR.

If many neighbors are skipped, power modulation bands can reappear (the kernel function no longer playing its local detrending role) and on the other hand if it is decided not to skip any neighbors, if the signal of interest are on several close frequencies or if the discretization is very fine (which is our case) it is possible that certain frequencies disappear (the kernel function is too restrictive in its role and only allows too prominent frequencies to pass) .

Once the SNR spectrum has been calculated from the spectrum, it is easy to select the stimulation frequencies from the frequency tagging and their harmonics and to average them to estimate the SNR.

2.3.5 Noise reduction

Noise and disturbances are therefore a central element of this kind of experiment and must be handled and minimized at all levels of the study. From the design to the method of analysis, including rigorous control of the environment, the experimental conditions and using an adequate preprocessing. A major influence is the number of subject tested and a right selection of interest area region of interest (ROI).

Evolution of the SNR with sample size

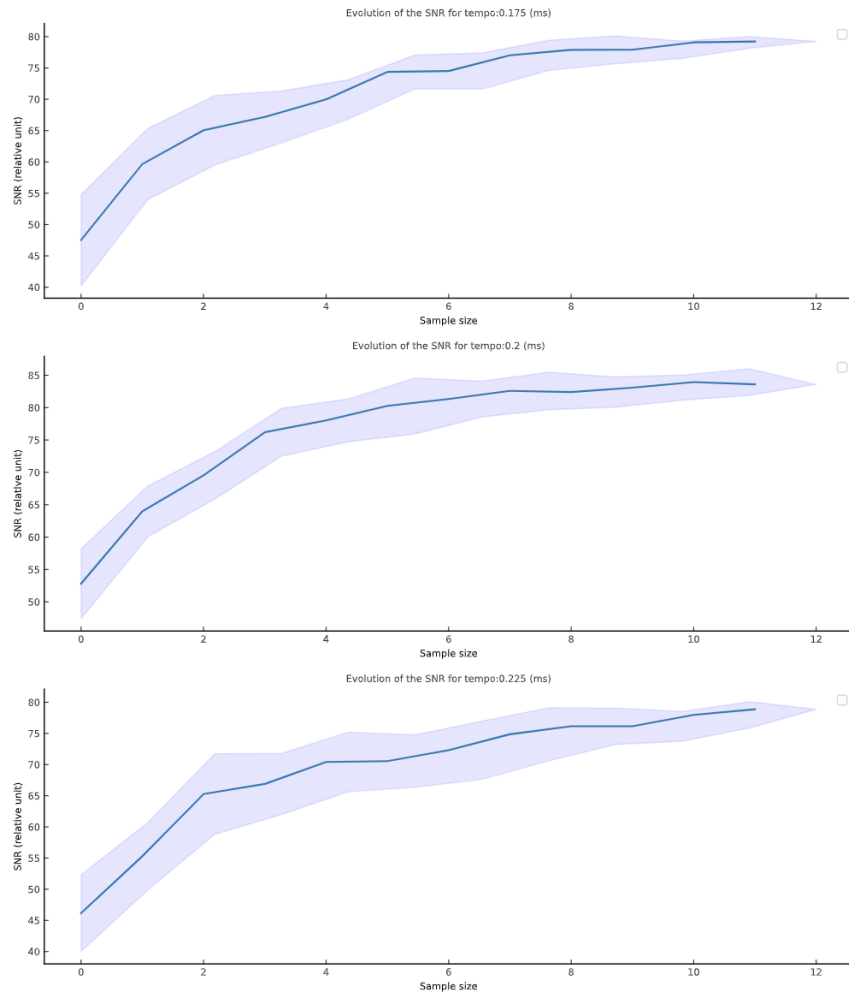


Figure 12: Figure showing the gain in SNR and the decrease in variability as a function of the number of participants tested. Top: variation of SNR for the fast tempo. Middle: variation of SNR for the medium tempo. Bottom: variation of the SNR for the slow tempo.

The number of participants has a major impact on the SNR fig. 12, tested with the frequency kernel method on the frequencies of interest.

3 Material and methods

3.1 Design of the experiment

The experiment aims to study how the brain synchronizes to a rhythm endogenously (1.2.4) and how the cognitive/behavioral response varies according to the tempo.

An approach based on the measurement of electroencephalogram (EEG) response is the "frequency tagging" method, the principle is based on the presentation of a stimulus at regular intervals. This regularity allows us to locate ourselves in the frequency domain thanks to the periodic response induced by this stimulus [35] (2.2.3).

The kind of stimulation used is auditory stimulus, which is a suited kind of stimulus for studying rhythm [40].

However, this is not the only way to study rhythmic processes and it exist also haptic stimulation using vibrational stimuli to induce a rhythmic response, there is an overlap between certain areas and responses but differences induced in particular by different neurophysiology [41].

Other indirect approaches to measure the perception of the beat and for the study of rhythms are based on the measurement of secondary neuromotor processes [4].

The secondary process measured is based on the production of movement and is recorded during a tapping task, at the end of the procedure during the experiment (3.2.2).

3.1.1 Montage

Wiring and setup are an important part of the experiment, good preparation, clean installation and adequate verification avoids most problems and oversights. A check-up list is established with a detailed protocol.

The topology is complex and must support the various parts composing the experiment. The auditory stimulation, the recording of data via EEG, and the acquisition equipment designed to the tapping task fig. 13.

MONTAGE DIAGRAM

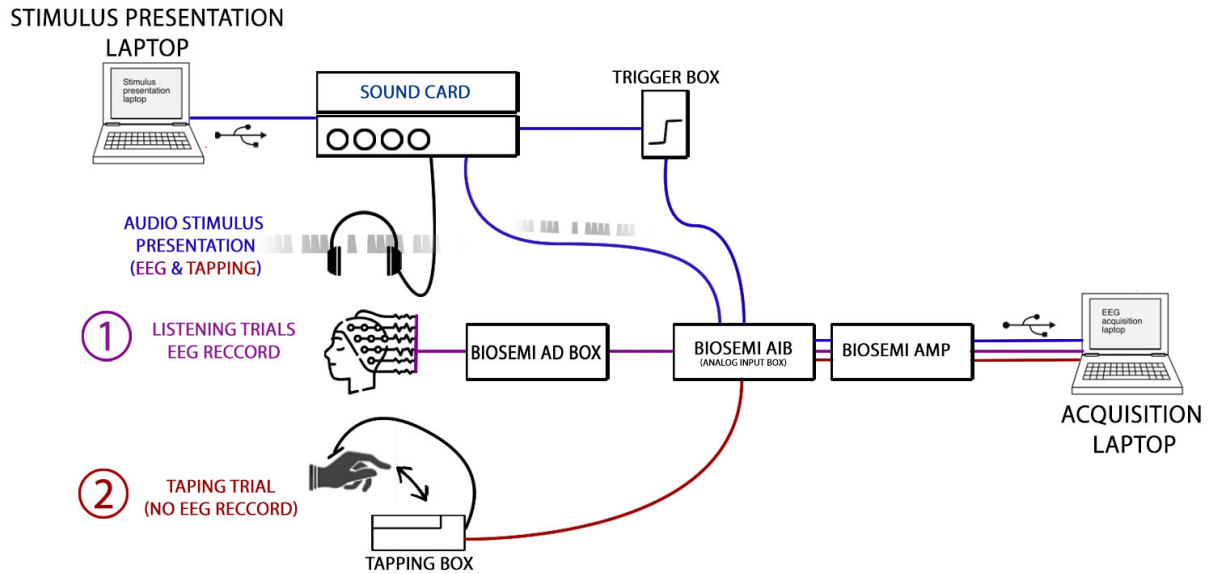


Figure 13: Simplified diagram of the wiring topology used for the experiment. Top: stimulus presentation computer, which is used to present the audio sequence but also to control the experiment by triggering the signals. The signal is replicated and recorded on an analog input box (AIB), an add-on box allowing the addition of analog signals at the same time as the recording of the EEG, making possible to centralize the acquisition.

For the listening trial (1), the EEG is recorded by electrodes and is transferred through amplifier - filter - analog to digital converter before being recorded via USB to the acquisition computer.

Below, tapping box, recording the tapping (2) by closing a current loop using an electrode put on the back of the hand. The signal also converges on the AIB add-on box and can be recorded at the same time as the audio signal on the same software as the EEG signal. The EEG signal is no longer recorded during this step.

All signals are recorded using acquisition laptop, parameters are generated by the stimulus presentation laptop, data are combined to be analyzed efficiently.

The first point of the system concerns the acquisition of EEG data which is done via many elements making up the man-machine interface (3.1.1).

Brain data recording As discussed during the presentation of frequency tagging (2.2.3), several modes of data acquisition are available [42].

The most suitable method is the recording of cerebral data through surface EEG if the purpose is to catch instantaneous response to the presented audio sequence.

This method has certain advantages and disadvantages, the main one is its high temporal resolution, allowing to capture details and fluctuations with a resolution of a millisecond (finer temporal resolution via a higher sampling rate is possible but not very relevant for

the desired application, also explaining the decimation of the samples during the preprocessing step fig. [26] [9].

The choice is made according to some criteria; this method is available, non-invasive and safe, exempting us to perform the experiment in a highly medical environment and under the direct supervision of a doctor.

It allows to recruit participants more freely and to have a larger sample of participants compared to a more invasive method, for example using intracranial electrodes, whose participants are recruited in an opportunistic way, are rarer, and are affected by diseases.

However, the recording quality and spatial resolution of the intracranial electrodes are more accurate [43].

The problems associated with the use of surface EEG are induced by the layers of the skull between source and electrode [9].

The signal is therefore strongly attenuated and varying according the specific impedance of each participant (the impedance varies in particular according to the composition of biological tissues, sweat, hair, contact made between conductive gel and the skull, ...) fig. [14]

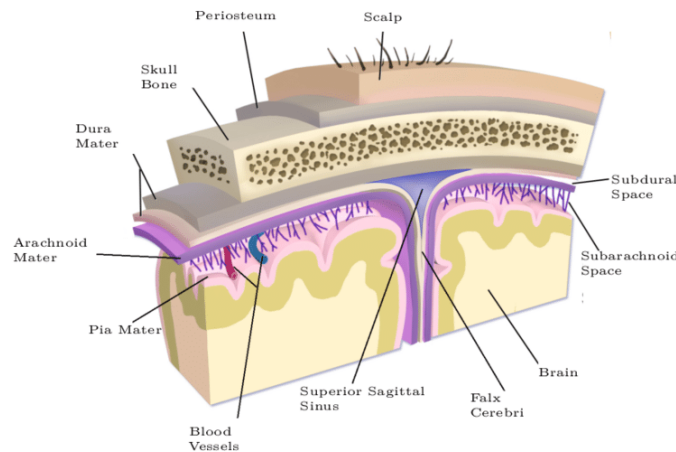


Figure 14: Representation [44] a schematic view of the different interfaces that the electromagnetic signal has to cross between its production resulting from a massive depolarization of populations of synchronous neurons and the electrode on the other side, in contact with the skin of the scalp.

In addition, electrodes are picking up any electromagnetic signal without discrimination, the signal is sensitive to noise and to all artifacts (2.3.5) (2.3.1) [36].

Another disadvantage of EEG is his poor spatial resolution [45]. This is due to the external skin contact position of the electrodes, by the approximation made that the head is a sphere. Moreover, the skull itself does not reflect the shape of the brain, which is divided into sulci, gyri and circumvolutions, that inside, finally the brain cannot be considered as a generator of uniform potentials but must be seen as a complex combination of connections and areas activating and communicating and therefore a synchronized action of neurons that finally provoking a strong enough depolarization to be captured by several electrodes.

Another phenomenon decreasing the spatial resolution of the EEG is due to the neighbors overlap of recorded signal [46].

The surface EEG therefore makes possible to have an idea (2.3) of the localization rather than a precise response [31] [4], to validate these intuitions other methods exist such as functional magnetic resonance imaging (fMRI). The fMRI allows in-depth exploration and more precise localization while being non-invasive but has less temporal resolution and is a much less available and expensive method, so it is complementary to EEG.

Surface EEG	Intracranial EEG	Functional IRM
High temporal resolution	High temporal resolution	Low temporal resolution
Low spatial resolution	High spatial resolution in restricted area	high spatial resolution
High availability	Very low availability	Low availability
Noninvasive procedure	Very invasive procedure	Noninvasive procedure

Table 1: Comparison of brain investigative methods.

EEG acquisition electrodes The acquisition of brain signals uses an EEG Biosemi Active-Two system (©Biosemi, Amsterdam, Netherlands) with 64 Ag-AgCl electrodes placed on the scalp according to the international 10/20 system.

Two additional electrodes are added at the level of the mastoids.

These two additional mastoids electrodes are used later for the referencing in the preprocessing pipeline, this referencing is done using average of mastoids electrodes as baseline and makes possible a better visualization of topography of signals recorded during the experiment. Because the active zones [47] are projecting perpendicularly to the cortical fig. 4. Previous studies [48] [21] show increased activity at the frontal level and on at the mastoid level (due to projection of the electromagnetic depolarization). A re-referencing by the average would therefore show several over-activated areas, reducing the readability and analysis of the data, this is therefore less suited that re averaging by mastoids.

These electrodes are active AG-AgCl wet electrodes directly integrating an amplifier 2.1, amplifying the signal before it is contaminated by noise coming from the equipment or from outside. The active electrode is a sensor with a very low impedance and the problems induced by cables and at the level of the hardware and connections are vanished.

There are 64 + 2 pin type electrodes, and two flat electrodes for the mastoids.

The Biosemi system breaks down the classic reference electrode into two electrodes, common mode sense (CMS) and driven driven right leg (DRL) which is a passive electrode.

It is forming a feedback loop by injecting a small amount of current to keep the potential of the participant as close as possible to the potential of the AD box reference, this improve the **common mode rejection ratio (CMMR)**.

The active electrodes convert the analog signals coming from the electrodes into a digital signal with a resolution of 24 bits and perform basic preprocessing, (record sampling rate at 2048 Sampling/sec with a decimation from 2048 to 1024 sample/sec) first order anti aliasing filter is applied before. The sampling rate may vary, for the experiment a sampling frequency of 2048 sample/sec is sufficient (the useful signal which is analyzed is only of the order of a few hertz in the frequency domain).

The AD-Box is electrically isolated and using independent battery, the data transfer is done via optical cable to avoid any electromagnetic disturbances.

The analog signal is carried to a USB receiver which is the hub and is the link with the PC. An analog input box is also connected to it, allowing information to be sent to the PC via the USB receiver.

This additional information are *triggers* and external signals, they are used to monitor auditory stimulation.

The LabView software allows to easily visualize all the channels recorded by the EEG, allowing a correction of the montage if necessary and allows to monitor the experiment. The data are recorded for analysis.

3.2 Overview of experimental process

The participants are comfortably seated in an armchair, they must fix a point to be as relaxed as possible fig. 10.

To reduce artefacts [49] and noise induced by muscles and brain interference the participant have to :

- Keep eyes open during trial, avoiding alpha wave generation,
- Fix a point and refrain eye movements, avoiding eye's muscles interference,
- Stay as relax as possible, avoiding unnecessary movement especially from muscles and head which can lead to massive interference.

The experiment last 2 hours and can be decomposed in 3 main phases fig. 15:

- A preparation phase, where lab is prepared, wiring is done, scripts and materiel are checked. Information is provided to participant and the setup of the EEG is done. Then test and correction are performed to ensure the quality and reliability of the setup,
- A listening trial, where audio stimuli are presented, and cortical activity is recorded through the EEG,

- A tapping trial, the participant have to reproduce a meter, based on personal perception, this is recorded through a tapping box (1).

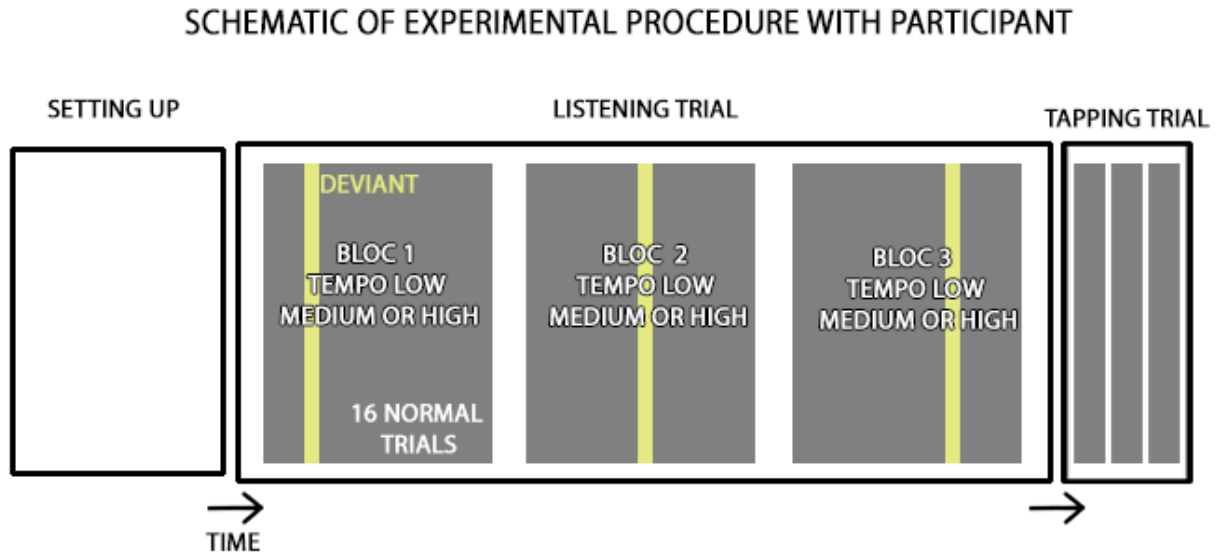


Figure 15: Diagram of the experimental procedure. Left phase: preparation phase of the experiment, cable and verification of the topology, explanation of the guidelines to the participant, installation of the participant and the equipment used for the EEG. Middle phase: a listening trial divided into 3 blocs where the audio stimuli are presented, there are 16 audio trials of the same tempo per bloc plus a deviant trial (in yellow) serving as a detection task for the participant. The tempo order of each bloc is chosen randomly from 3 tempi available, there is no repetition of the tempo selected between blocs (the 3 tempi are played, the order may differ). Right phase: tapping trial, serving as a task for behavioral detection of the perception of the measurement by the participant, there are 3 blocs each composed of 2 trials. The tempo in each bloc is also chosen randomly without repetition.

3.2.1 Neurocognitive task: listening trial

Audio stimulus The stimulus used is an audio stimulus as a sequence composed of 12 elements fig. 16. These elements can be silences or audio signals with a square envelope and modulated via a **Pure tone** sinusoidal type carrier at 200Hz (fall time 45-55 ms following tempo and a rise time of 10 ms).

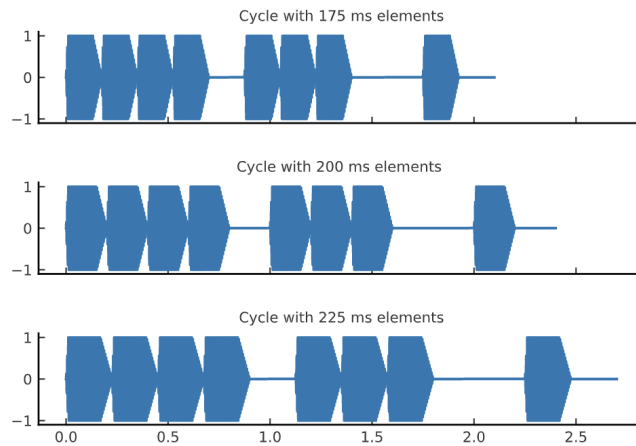


Figure 16: Representation of the pattern cycle, Top: fast tempo, middle: medium tempo, bottom: slow tempo. This is the pattern making up the sequence presented to the participant during the listening trial and the tapping trial.

The stimulus pattern is therefore composed of 12 elements which can be silences or sounds event and form a pattern fig. 16.

AUDIO PATTERN (1 CYCLE)

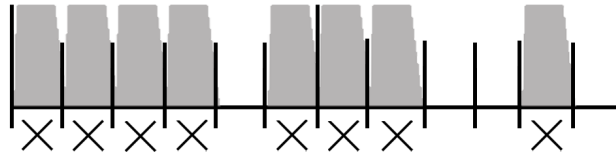


Figure 17: Audio pattern with representation of audio stimulus, this pattern is composed of 12 events, sound and silent events. A repetition of pattern cycle (17) is composing the auditory trial. The event time can change following desired tempo, 3 different tempi are used, 175ms/ event tempo, 200ms/event tempo and 225ms/event tempo for a total duration of the period of 2.1s, 2.4s, 2.7s.

This pattern cycle is repeated a certain number of times during the trial. This pattern is designed to specially to not express any very prominent magnitude on its spectrum, when he is repeated to for a Sequence.

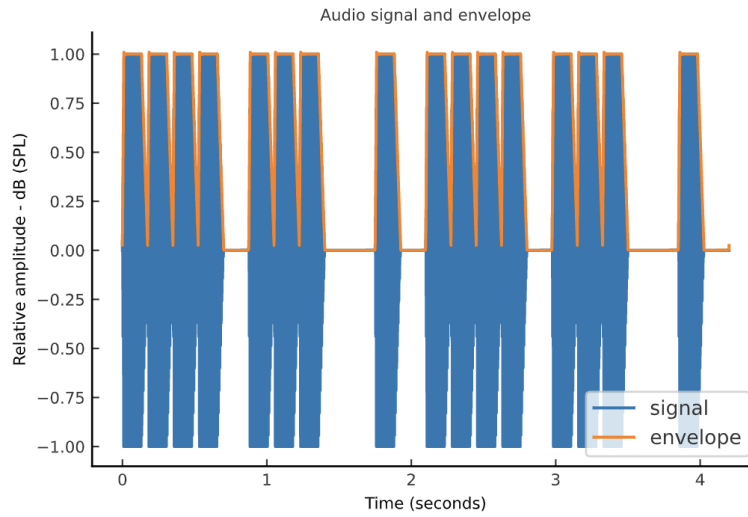


Figure 18: Representation of two pattern cycle with the real envelope representing the analytical signal (without carrier at 200 Hz)

Frequencies composing this sound, it is first necessary to come back to the baseband, a demodulation of the signal to remove its carrier at 200 Hz is done. A Hillbert transformation is done, extracting the envelope of the signal.

Once the envelope has been extracted, it is possible to visualize the spectrum of the sequence by applying a DFT implemented via FFT.

The spectrum is made up of peaks and frequencies spaced out by regular intervals.

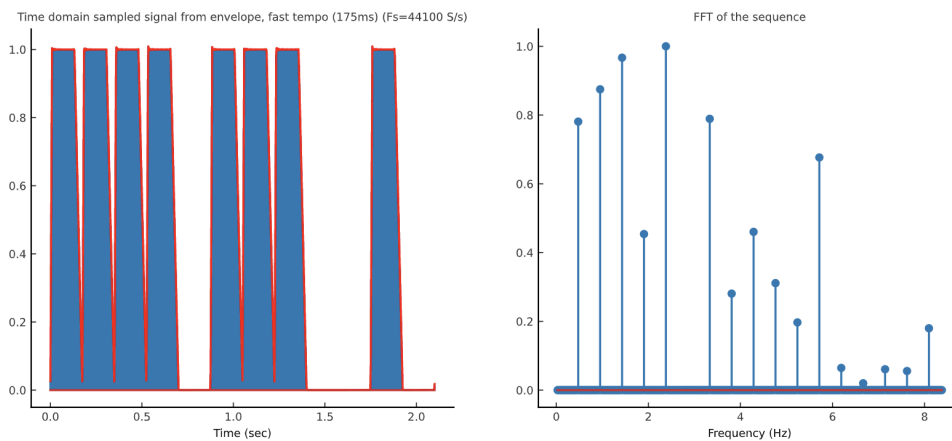


Figure 19: Left: Analytical signal of a pattern cycle (red) positive value of signal with pure tone sin at 200Hz carrier. Right: DFT of the whole input analytical signal sequence normalized.

The fig. 19 shows the analytical signal of the pattern cycle at fast tempo (175ms), le DFT correspond to the spectrum of the envelope of the whole presented sequence, frequency

disposition are also found in the EEG response, but amplitudes are transformed at these frequencies [23] (2.2.3).

The pattern cycle is looped continuously during the trial, composed of a repetition of N cycle = 17 times the pattern fig. 20. The number of repetitions of this pattern comes from a preliminary stage in the design of this experiment of optimization of the parameters resulting from a reflection and analyzes to optimize the noise while keeping a supportable duration of experiment for the participant and to keep his focus [50] (3.3, 1.2.1, 4).

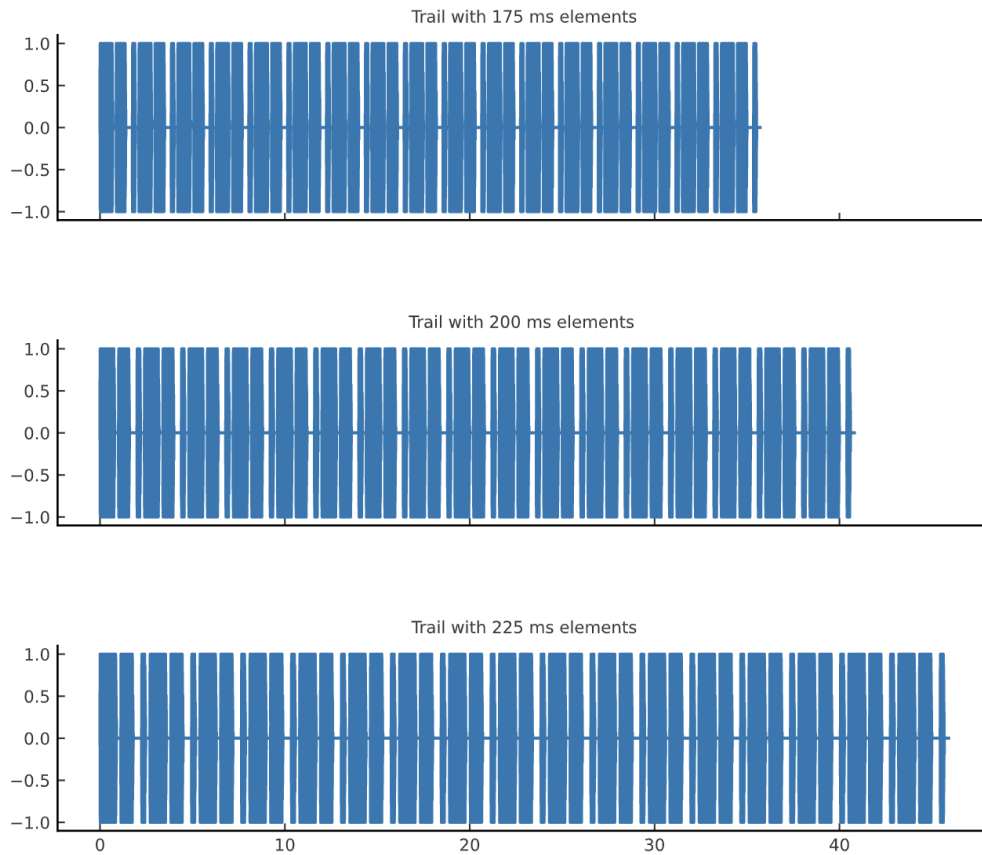


Figure 20: Representation of the entire sequence presented to the participant during the listening task, and the tapping task. The sequence is composed of $N=17$ repetition of the pattern cycle fig. 16. The duration therefore varies according to the tempo. Top: fast tempo, middle: medium tempo, Bottom: slow tempo

For the listening part there are 16 trial repetitions per tempo fig. 15.

The waveform polarity of audio sequences is reversed between trials, to prevent electrical potential artifacts at the frequency of the audio input [36].

Finally, there are 3 different tempi, the tempo corresponds to the speed where the trial is played. There is a slow, a medium and a fast tempo 1.2:

1. The fast tempo has a time to play each element⁴ of 175 ms, the elapse time of the trial is 35.7 7 seconds long⁵.
2. The medium time cycles through the elements with a period of 200 ms, the elapse time of the trial is 40.8 seconds long. .
3. The slow tempo cycles through the elements with a period of 225 ms, the elapse time of the trial is 45.9 seconds long. .

There are 3 tempi that have been specially designed to be compatible with a range of perception and spontaneous generation of the beat (1.2.3).

If the tempo is too fast and the pattern repeats too quickly, the brain tends to "decimate" the listening naturally and perceive a tempo with multiple periods [6] [25].

The same is true if the tempo is too slow, the integrating effect of the brain is lost. The brain is then no longer perceiving the sequence in a global sequence but as separate and inconsistent events, making it difficult for the participant to generate a rhythm endogenously.

[11] The purpose of this study is therefore to investigate the change of the EEG response with the variation in tempo while remaining within an human range of meter perception [25].

Initially the experiment tested 5 tempi but to optimize the signal to noise ratio (SNR)/comfort and maintaining the participant's attention [21] it was decided to reduce to 3 different tempos instead (3.3).

The listening phase is therefore composed of 48 regular listening trials, to which we add a so-called fixation task (3.2.1). Raising the number of normal listens to 51 fig. 15.

Presentation of the audio stimulus The stimulus presentation computer drives the experiment using a matlab script fig. 13.

The computer sends the audio sequence to an external sound card which correctly modulate the sound, copy the audio signal, and distribute it to the earphones adapted to the EEG.

And to send another copy of the signal to an analog input box connected to an analog to digital converter (ADC) itself connected to the acquisition PC via the proprietary Biosemi software allowing the connection between the boxes of the Biosemi suite and the PC. The advantage of recording the sound at the same time as the EEG is to easily have the same benchmarks and to be able to monitor everything from the acquisition PC.

The audio stimulus is presented to the participants using electromagnetically shielded in-ear headphones so as not to disturb the EEG acquisition during the first part of the experiment (at 75db sound pressure level (SPL)) (ER 2, Etymotic Research, Elk Grove Village, IL USA).

The stimulus presentation computer also sends signals directly to the analog to digital

⁴There are 12 elements that form the pattern, so 12 elements per cycle and 17 cycles per trial)

⁵ $T = 12 * 16 * 0.175$ seconds

converter (ADC) BioSemi box connected to the acquisition computer fig. 13 allowing to know the trial starting time. This signal is important for the analysis steps to have a time mark where the signal must be cut in epochs.

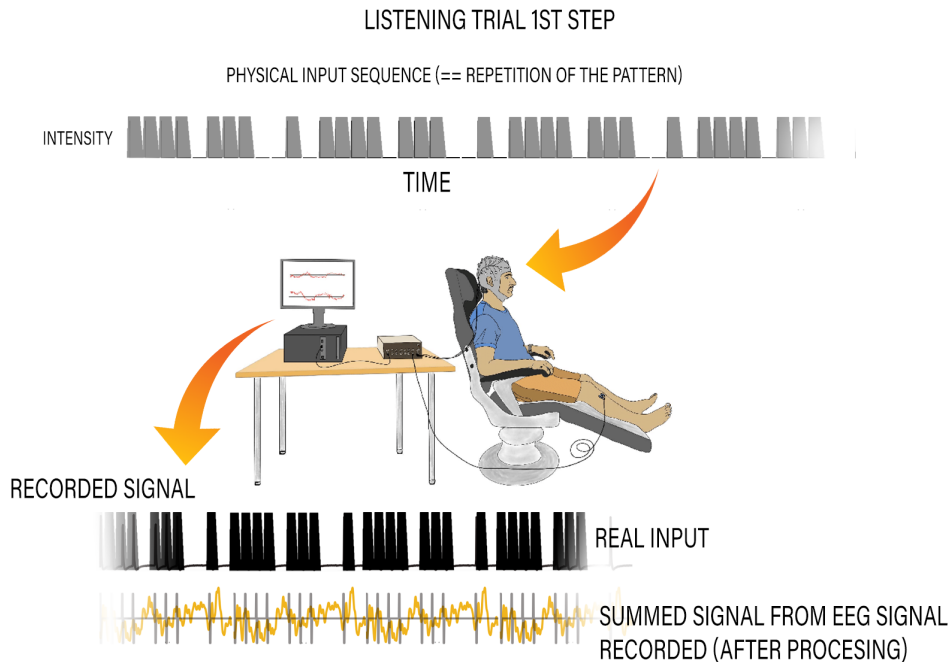


Figure 21: Listening trial (1): The subject is immobile and fixing a point, his only task is to listen carefully the sequence (top). While listening, his response is recorded using electroencephalogram (EEG) (mid). The subject listens 3 the sequences at 3 different tempi. The subject listens 16 times the same sequence (at the same tempo). After this, the recorded signal is processed, cut into epoch and can be submitted for further analysis, and to explore the influence of the different tempo and to explore the endogenous representation of the pattern related using the information given by the second step of the experiment.

Detection task The Detection task gives an achievement to the participant during his listening task. The purpose is to maintain the attention focused during the audio sequences. The participant must focus on the temporal aspects of the rhythm in presented audio sequence and listen carefully, the participant has to report after each trial if he has heard a deviant.

The task is to detect a change in tempo intra-trial (during a single trial).

This tempo shift is temporary and concerns only one pattern cycle (so 1/17 th of the trial time).

The tempo variation is quite light (therefore difficult to perceive), the tempo shift is around 13% and the attention is required to detect it [51] [21].

The shift lengthens the duration of the element constituting the cycle, therefore decreases the tempo.

These trials are rare because they are not usable during the analysis, there are only one deviant trial per trial bloc grouped by tempo, for a total of 3 for the whole experiment (3 tempi).

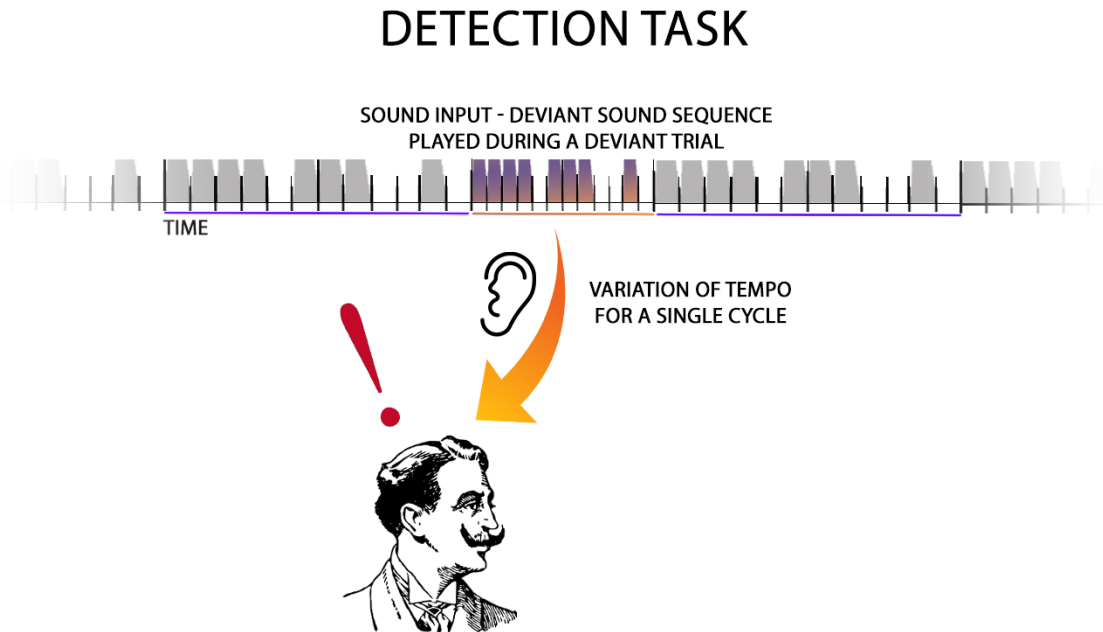


Figure 22: The participant has to listen carefully to the presented input sound. If a deviant sequence i.e. a shift of tempo during a cycle, is detected, the participant has to report it to the examiner at the end of the trial. The purpose of this kind of task is to maintain the participant's attention during a long lasting experiment.

Experimental procedure of the listening trial The listening phase consists to 48 trials where the stimuli from these 3 tempi (3.2.1) are presented.

The experiment is using a bloc design for stimulus presentation. Each bloc is made up of 16 trials at the same tempo plus the detection task which is also an deviant audio stimulus fig. 22. The arrangement of the blocs (so the order of tempo) is random between each participant, as well as the position of the fixation task in each bloc fig. 15.

The listening task is done using the EEG acquisition equipment, the participant is therefore limited in his movements also between the trials (when he is allowed to move without biasing the recording).

Each trial starts with a few seconds of silence (5 seconds to get 3 proper seconds), followed by the stimulus lasting 35.7 seconds - 40.8 seconds - 45.9 seconds depending on fast-medium or slow tempo respectively.

Audio sequences are presented with electromagnetically shielded headphones avoiding hardware-induced electromagnetic artifacts.

The supervisor is present throughout the experiment and oversees launching each trial,

when the participant feels ready. At the end of each trial the experimenter takes note of the participant's remarks and notes whether the trial included the fixation spot which consists of momentary irregularities in the tempo (the tempo changes the duration of a single cycle during the trial).

3.2.2 Behavioral task: tapping trial

A second approach to measuring the internal representation of meter and beat rely on the measurement of secondary processes [1] (1.2.4).

During this second part, the experiment corresponds to a behavioral study, where the participant must perform a motor task.

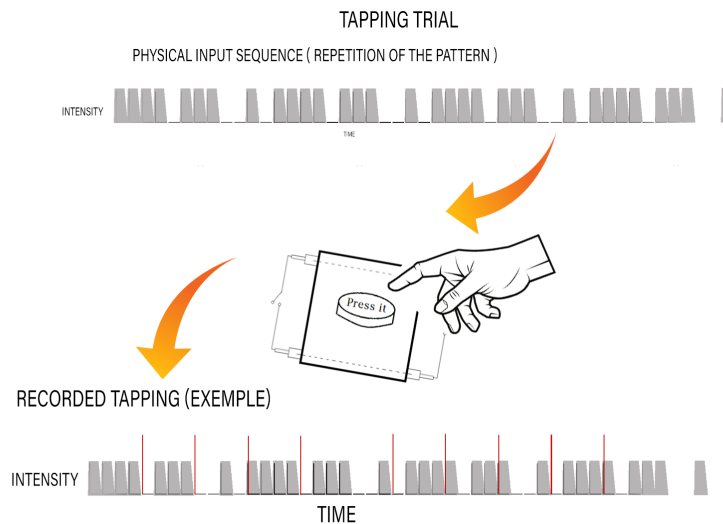


Figure 23: Tapping trial [1]: the subject has to listen sequences (same sequences than the listening trial) and try to perceive meter and beat in played sequence. The complexity is that the input sequence (top) is composed of pattern that doesn't induce beat in an exogenous way, so the subject has to generate an internal (1.2.4) representation of a meter and beat, and tap on a "tapping box" based the internal perception of beat and meter, corresponding to the red bar on bottom sequence (tap representation on the input pattern). This trial is specially designed to explore this endogenous representation of the rhythm and to compare this rhythm with electroencephalogram (EEG) response from first part of the experiment (the listening trial) [1].

There are certain assumptions with measurement via secondary process to keep in mind [1]:

1. The process changes dynamically over time reflecting the immediate ability to adapt and respond to instructions given to a situation and correct where necessary,
2. These dynamic processes can be measured with a sufficient temporal resolution (it is the case here it is a phenomenon of the order of the hertz therefore easily measurable,

3. This phenomenon is supposed to be coupled in a one to one way with the internal representation of the meter.

The movement as secondary process is already very linked to the rhythm (perception and expression) in usual life [1], there are therefore already strong connections between the perception of a rhythm and movement and there is also a great suspicion of coupling at the cortico-subcortical level [52] [22] [48], this advantage is used in this experiment.

In addition, the explanations are simple, intuitive and quickly understandable for human participants (this is harder with animal models [1]).

The recording is done via a box specially designed for this kind of application.

This element is the *tapping box*, necessary for the behavioral tapping trial record fig. 13

This external box consists of a pressure sensor, allowing the tapping force to be recorded (which is not used in this experiment), the signal passes through the analog input box and is recorded on the same software and in continuity than EEG information.

The box is also designed with an electrode, this electrode must be placed on the participant's back hand.

By touching the metal plate of the tapping box, the participant closes a current loop triggering the detection of contact and triggering a signal which also pass through a BioSemi amplifier box and be recorded on the same software (Actiview from BioSemi).

This centralization and synchronization between the tapping sound and the start of the trials (listening and tapping) is the cornerstone of an effective analysis to understand the periodic processes induced by the audio stimulus.

Two audio sequences are composing each blocs presented to the participant at each tempo (for a total of 6 trials), the participant is invited to tap according to the rhythm that seems natural for him fig. 15

The behavioral task is implemented to see if the person is indeed able to find a coherent and stable rhythm according to the periodicity of the cycle.

During the second part of the experiment, the EEG response is no longer recorded because it is corrupted by the movements of the participant.

Tapping and beat hypothesis The starting hypothesis: the participant taps regularly a number N times per cycle (N being an integer) which is a sub-period of the stimulus period (therefore the inverse of the harmonic of its period), this period of tapping is also linked with its perception of the meter and beat [1] (1.2.1).

This is based on previous studies hypothesizing that secondary processes would mimic the internal representation of the meter [53] [10] (1.2.4).

The participant has to tap at a constant subperiod of the period of repetition of the pattern (the time of the cycle), if the pattern is divided into $N=12$ elements, the participant tends to group the elements by 4, to tap 3 times per cycle at medium tempo for 2.4 seconds (200ms for each element) (1.2.1), the regularity is important.

A faster tapping is difficult and no longer seems to be a natural representation of a rhythm, it could be a copy of the pattern heard, which is not the purpose of the study and must

therefore be corrected by the experimenter who have to re-explain the objective of the tapping task [54].

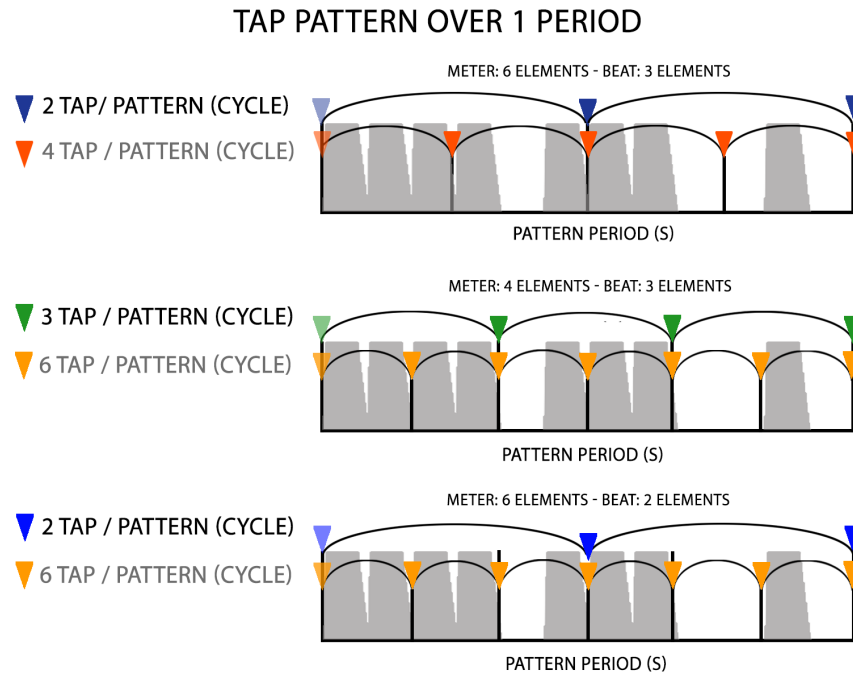


Figure 24: Classification of theoretical meter and beat perception for a 12 element pattern presented.

A previous study [10] shows modifications in the tapping behavior when multiplying by two and then by 3 the tempo, showing that a high proportion of the participants tapped once every 8 and 12 elements (the grouping of element increase on adaptation to the tempo speed up) when the tempo increases drastically, the hypothesis announced is the preferential beat frequency range and the integrative capacity of the brain to group together X elements of the patterns to find a beat in its preferential range (1.2.3).

Analysis of the tapping results have to verify if this trend exists, and if there is significant variations of this trend for smaller tempo changes.

For the fast sequence, with a cycle of 2.1 seconds (0.175ms per component), i.e. a drop in tempo of approx. 13%, a hypothesis would be to see a change in tapping, every 6 elements (2 tapping per cycle) instead of 6 (H1), it is on the contrary possible that the tapping every 4 periods is always in the range and does not change the number of trappings (H0).

For the slower sequence, 2.7 seconds (constituent elements of 225ms) the alternative hypothesis (H1) would be to observe 4 taps per cycle, i.e. one tapping every 3 events. Similarly, if we are still in the preferential beat frequency range, it is possible that there is no change or that it is not significant (H0).

Experimental procedure of the tapping trial The tapping trial comes at the end of the experiment after the listening trial, the participant is therefore relatively accustomed to the sequence played and has been attentive to it for already about 50 minutes (at this stage of the experiment) fig. [15].

The task of the participant is to listen carefully to the sound played, once the participant finds a rhythm, he must tap as regularly as possible and in sync with the audio sequence. There are a total of 6 trials for tapping with 3 different tempi, these tempi are randomly distributed in blocs of two among the 6 trials.

It is asked to listen carefully to the sequence played which is also the same repetition of pattern and to try to detect a beat and meter in the played sequence.

During this tapping trial, the participant is invited to move, put himself in rhythm and close his eyes if he wishes to promote deep understanding of the audio sequence and to help him find a rhythm consistent with his hearing [55].

The participant has to focus to understand the rhythm of repetition of the pattern, and to use his endogenous ability to generate a rhythm [15] modeled on the period of the pattern heard.

In this way he could be able to perform the behavioral task and tap on the tapping box.

The task is not so easy because the pattern used does not express a prominent frequency apart from the cyclical repetition of the pattern. There are therefore no perceptual (physical) indices when to tap.

The participant can take his time to analyze/synchronize himself to the rhythm before tapping.

The purpose is to be as regular as possible and to stay in sync with the pattern according to the perception of the beat and pattern of the participant. Someone regular but not in sync with the pattern repeat period is shifting out of phase.

The behavioral task is not used to analyze cortical data but is used to understand if the participant is able to perceive a beat, to stick to it and allow to compare the elicited rhythm to the theoretical rhythms.

As this task is not trivial, it is possible to start again until the participant and the experimenter are satisfied.

The participant can repeat the trial several times if he wishes and if he does not find a suited tapping period the first time, as a reminder fig. [52b], the sequence is composed of complex pattern which is not suggesting a beat, the task is therefore not straight forward unlike a unique and periodic sound sequence.

3.3 Development of the procedure and legacy

The design of the experiment has been initiated in 2020.

The first tests on colleagues (non-naive) and on the first participant (naive) have started at the beginning of 2021.

The first refactoring concerned the changing of parameters influencing the length of the experiment .

the following changes have been done: reduction in the number of tempi tested from 5 to 3. Adaptation in consequence of the number of tapping trials from 10 to 6 (two trials per tempo).

The choice made for the former sound element of the pattern was a Dirac pulse (3.2.1) known as click impulse.

Continuation of laboratory tests during the summer of 2021 debug and addition of a detection task (3.2.1) consisting in detecting a slight change in tempo on one of the cycles during a trial

During the Fall of 2022: acquisition of the first sample of 10 people under the conditions described and under supervision.

During the first analyses, it turned out that the EEG responses to the acquisitions were noisy and it was decided to return to a more basic type of impulse and already used in previous experiments studying the rhythm.

Despite a substantial number of acquisitions, it has been decided to change the former element of sound constituting the pattern and to return to a square signal composed of a square envelope signal and composed of a sinusoidal at 200 Hz with an attack slope of 1.5 cycles (7 ms) and a slope of 9 - 13 cycles (varying with tempo) for 25-32 cycles of perfect sine waves at full amplitude.

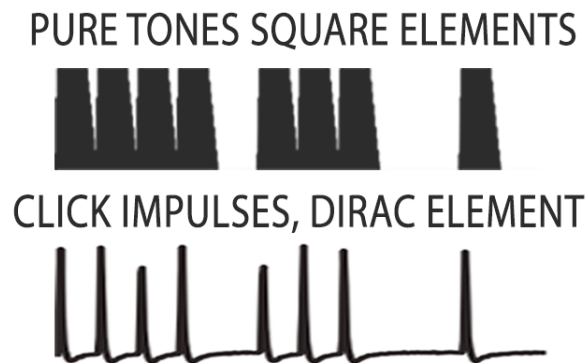


Figure 25: Comparison in time domain of click element versus pure tone square element composing a pattern (3.3).

The underlying phenomenon inducing the noise is not well known and various tracks must be explored in the future.

The previous acquisitions are kept for a future study of the disturbing parameter.

During the spring and summer of 2022 acquisition on the cohort of 13 participants.

3.4 IT and analytics architecture

3.4.1 Architecture of the pipeline

Intelligent software design responds to certain "problems" or rather to facilitate the implementation of certain features while respecting and maintaining the healthiest possible software architecture and in accordance with the principles of expandable and maintainable development, an additional constraint is that the architecture used must facilitate the processing of massive data [56].

Batch sequential approach The architecture used for the development of the analysis pipeline is based on the Sequential Batch principle, The principle is to create sub-systems that are able to follow one another and transform the data.

Each subsystem is therefore a stage in the analysis of the data which transits in the form of a packet.

In this first case of figure we try to keep a certain atomicity between the batch, it is necessary to process a quantum of data before being able to move on to the next step, i.e. in a another subsystem of the chain.

Usecase This data-oriented architecture is perfectly suited to our use case, processing is necessary to interpret data. In addition, the use of transaction by package and the subdivision into clear sub-systems makes it possible to have feedback directly on intermediate data. These splits and feedback increase application debugging, understanding of the chain of analysis.

These divisions return increase the decoupling of the application, the understanding of the analysis chain. This increases the speed of creation because it requires no longer the final result to correct some problems.

It relies on a small number of large independent subsystems that are executed sequentially, ideal when analyzing large files.

Pro:

- Weak coupling of the subsystems, in theory only the data pass through them,
- Simple division of subsystems,
- Chaining and intermediate data do not make it necessary to keep a global state, these subsystems can run on different machines, therefore, without fear of side effects.

Disadvantages:

- High latency, which causes a low data rate at the end, we have a certain bottleneck when expensive processing,
- Very linear structure format Input, processing, output (repeated N times),

- No competition with respect to the operation, the parallelization of the architecture is difficult, unless the chains or subsystems are duplicated. The processes are separated, due to the principle of atomicity inherent in this architecture.

Pipes and filter approach It is an evolution of the previous system (3.4.1), in the system of pipes and filters there is incremental transformation by the components.

These components are connected, and data passed from flow according to first input first output (FIFO) logic.

The flow is seen as continuous, and it is therefore the entire file that is exchanged. The downstream subsystems can therefore start their analyzes very early to transform the data, the filters can work at the same time.

Advantages:

- The output is produced incrementally without waiting for the end of the output,
- There is a non-concurrent execution of the components (there are no blocking between them),
- Pipes are stateless and simply carry the data stream.

These filters are seen as a step in the processing of information in the general sense (to be distinguished from the filters applied during the preprocessing which have a more reduced and more precise meaning). To be part of such an architecture, these filters must respect some criteria:

- They must be independent of each other, they must not have any state (therefore keep an identical processing behavior, without worrying about causal parameters) and must work in a naive way, i.e. ignoring their neighbors and their connection,
- The classic point of view where the data is retrieved, processed and written in output, (like UNIX pipes), these filters are qualified as active, There are two types of filters against the data:
- The classic point of view where the data is retrieved, processed and written in output, (like UNIX pipes), these filters are qualified as active,
- Some filters are nevertheless qualified as complex, because they retroact by requesting output information from the previous filters to process the incoming data. (the usual example is of a compiler that needs to know what happen as a token, to make decisions).

Pro:

- Very good throughput, and possibility of accelerating via parallelization (massively parallel matrix analysis is precisely the specialty of GPUs because it is very similar to graphical analysis of shaders, etc.),

- It is reusable because it is segmented in this architecture (and more continuous in the analysis of the data), it is therefore also more easily maintainable than a monolithic bloc, these are the advantages of having an architecture naturally exhibiting weak coupling,
- Evolution/ adaptation is easy.

Cons:

- No direct interaction between the filters (interaction by data), which increases the rigor of programming,
- The data must have a common format, so consistency must be maintained in the data,
- There is very low fault tolerance, if a single filter bloc, the pipeline is blocked and data is lost/hardly reusable, leading to low atomicity regarding data management.

Other cousin architectures of these exist but are more adapted to on line processes and requiring real-time control and therefore much less adapted to data analysis.

Comparisons of architectures Batch sequential:

- Handling large components, coarse grained,
- High latency, high-level parallel analysis is also much easier, calculations on intermediate components can easily be transferred to several machines while guaranteeing data integrity,
- External access to files each filter produce intermediate data, which is ideal for debugging, for quality control and auditing, the process is very transparent,
- No competition.

Pipe and filters:

- Small components (fine grained),
- On-the-fly processing,
- Localized data,
- Possibility of competition.

The pipeline is implemented according to a sequential batch perspective, there are different stages that process our data; Intermediate data are recorded and make possible to analyze and fully understand the involvement of the different stages.

This principle is useful in the comparison of the different algorithms implemented.

3.5 Implementation of the architecture

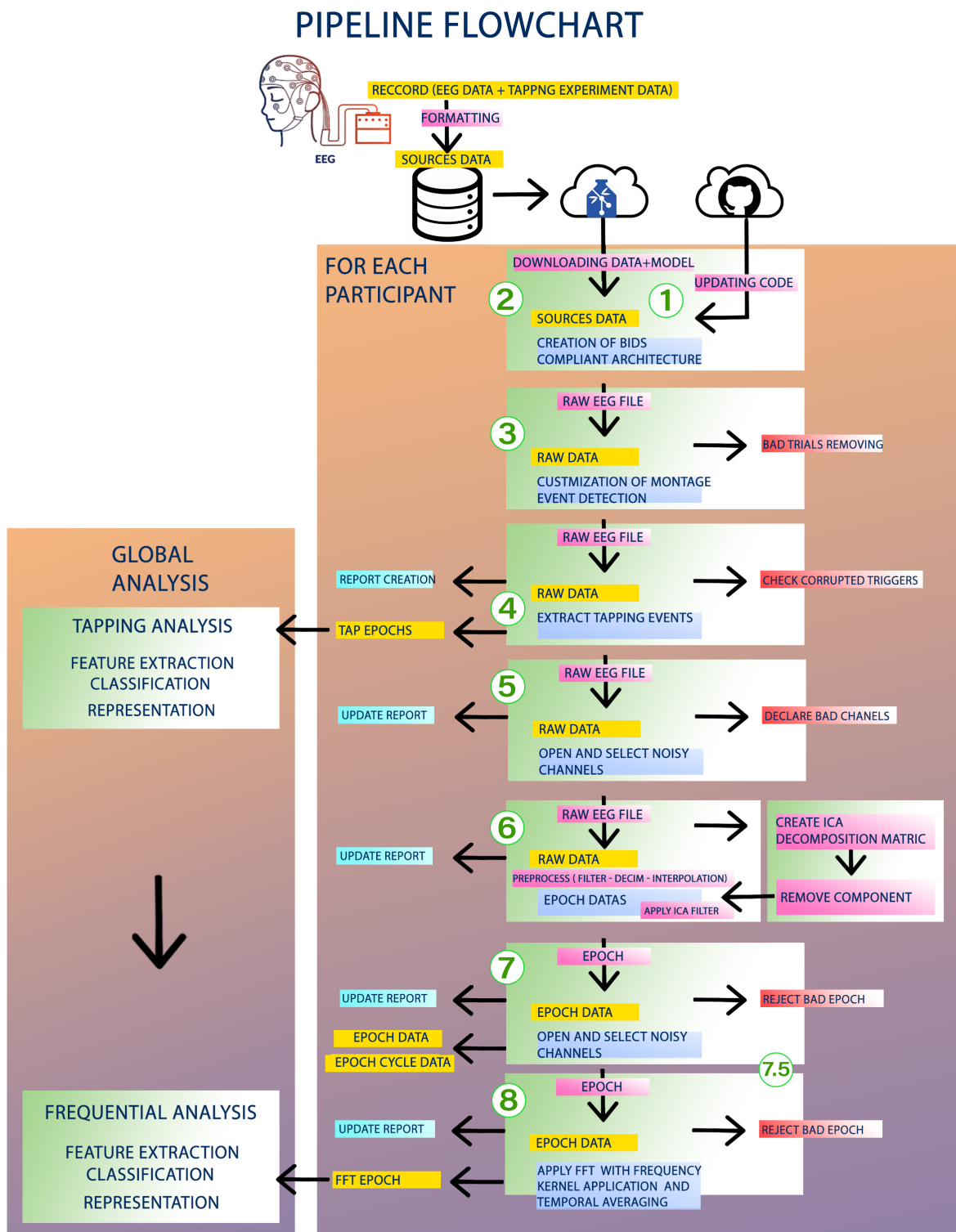


Figure 26: Sum up of the pipeline architecture. Blue: summary of the step, Pink: data processed, Yellow: data obtained, Red: data filtered/discarded, Cyan: audit information, Green: implementation bloc. August 19, 2022

The architecture follows the pipeline pattern. The implementation is done using mainly Python (3.9.03) [57], the idea is to use the latest standards in terms of data management and the latest technologies in terms of framework and to train there.

In addition, the general idea is to have a pipeline handful for teamwork, an emphasis has been placed on the scalability of the code and on shared development to facilitate collaboration

The whole pipeline is destined to evolve in future iterations of this project.

It is decomposed in many steps to ensure an easy and clear vision on processing and analysis of data.

3.5.1 Downloading data

The first step fig. 26 (1) is to pull and download the codes annexed to the project, such as the codes used for the experimental management of the trials, or the data relating to a biosimulation.

These data transits via the GitHub API and are stored in an online repository GIN.

The pipeline also makes sure to have downloaded the Datalad (a reference managing system) references to download large files.

Datalad serving as references pointing to a GIN online repository system, allowing the storage of large amounts of data, such as data from neuroimaging. Still in the philosophy of collaborative work and future data sharing.

The existence of project directories is ensured beforehand and are created if necessary.

3.6 Pull data from source

This is the step fig. 26 (2) for massive downloading of data from the EEG, the tapping test and the experimental parameters.

The arborescence is created according to new standards called **Brain Imaging Data Structure (BiDs)**, giving the directives to structure the data resulting from neurosciences allowing a better structure and allowing an easy interoperability.

Via datalad references, data are downloaded from an online store repository GIN.

Once the download step is done, a check on name convention is carried out to ensure that the conventions are respected and conform to bids standards.

3.7 Cleaning raw data

The data from the EEG fig. 26 (3) are read to recover the events that took place during the experiment,

The EEG 10/20 biosemi assembly is slightly modified to respect the Electrode naming convention, and to add mastoid electrodes which do not appear in the standard assembly.

A series of verifications is performed to ensure the integrity of the data, as the triggers signals, which are the signals used to situate oneself in the experiment and used as time

reference.

They allow to detect when a trial has started, what type of trial and what tempo is selected. This message channel is used for the second part, the tapping trial, to notify the start of a trial but also to record the participant's tapping activity.

The trials marked as bad are removed from the list and are therefore not considered in the future, considered as useless signal.

A reporting system is also in place to quickly pull information from the pipeline and extract essential information in a visual and shareable way.

3.8 Extraction of data from the tapping test

The EEG file fig. 26 (4) is compared to another file to retrieve tap in a separated dataframe. Checks are process to remove ghost signals and signal repetition this is the drawback of using analog signals for event declaration, 2 signals are stackable and can lead to a errored signals.

3.9 Selecting bad channels

Data are visualized fig. 26 (5) and reviewed throughout trials.

If an electrode is noisy or has problems that could corrupt results, it is possible to declare it as bad.

This is a semi-supervised way to select bad channels. Future methods are being tested to automate these steps using specific dedicated libraries or filters to verify the integrity and reliability of the electrode signal.

The automatic methods to detect a bad electrode is done by making pairwise comparison with the neighbors, because the neighboring electrodes must have a similar behavior [31] [58].

Other algorithms are based on the relative stability of signals, this one express measurable artifact such as signal amplitude jumps, slow drift or increased variance.

3.10 Preprocessing

Channels marked as bad fig. 26 (6) are then linearly interpolated using neighbors.

The re-referencing of the EEG is done using the mean of mastoid electrodes.

The data are first filtered, high pass at 1 Hz, and low pass at 40 Hz via a hamming filter for independent component analysis (ICA) [59].

The ICA is made only for the trials of the listening phase, whose EEG response is useful. Components are plotted and manually selected.

The selected components are then removed. These components are mainly stereotyped artifacts such as blinking and gaze aversion. The approach remains quite conservative to

keep a maximum of useful signal.
The modified ICA matrix is saved to be applied as a filter later.

3.10.1 Filtering and decimation

The first step is to filter our signal.
The high pass filter must be applied at low frequencies because the signal studied is of the order of a hertz (52b).
The low pass filter can be a little less strict, given the sampling frequency of 2048 samples/Second the frequency could theoretically go up to kHz, but our interesting signal going up to 6 hertz, it is possible to place the low pass filter at some ten hertz and therefore to remove a large part of the spectrum which is useless in our application and in the analysis. However, we must be careful with a high pass filter which can induce ringing artifacts. It is also possible to decimate the acquired signal to reduce the data, a factor of 4 seems appropriate, allowing the analysis to be done much faster while preventing aliasing and ensuring the quality of data.

3.10.2 Application of the ICA

The ICA decompose the signals into independent components by source.
It is possible to select certain components associated to artifacts. Once removed, an inverse transformation on the signals is applied to the data, having the effect of removing the associated artifacts in the "sensor space".

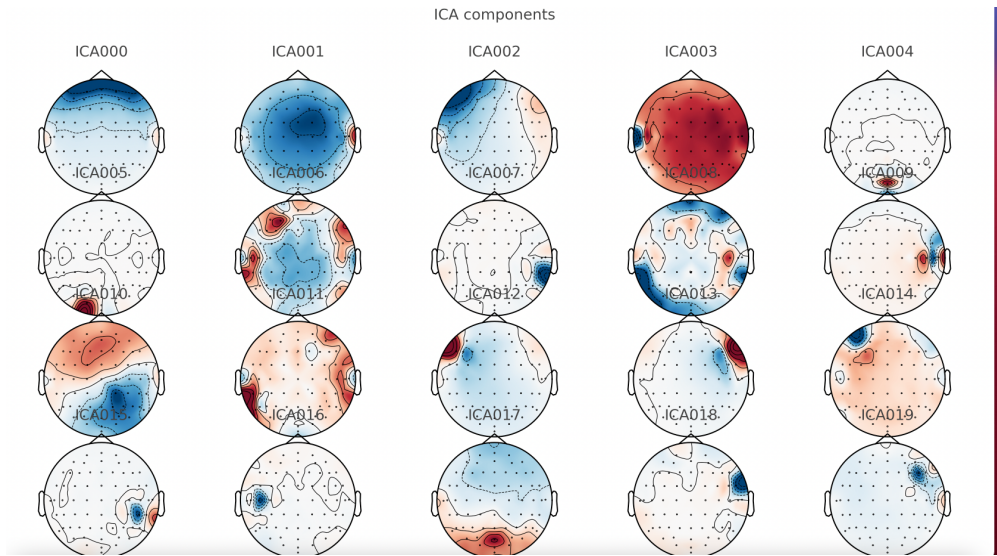


Figure 27: Global view of the different independent components, each signal is represented topographically and sorted according to the variance explained by the independent components. ICA000 (top left) shows a strong signal in frontal area, ICA002 shows antagonist frontal signal between right and left.

Example of signals removed A typical and spatially very localized disturbance is eyes blink, causing strong polarization/depolarization at the frontal level.

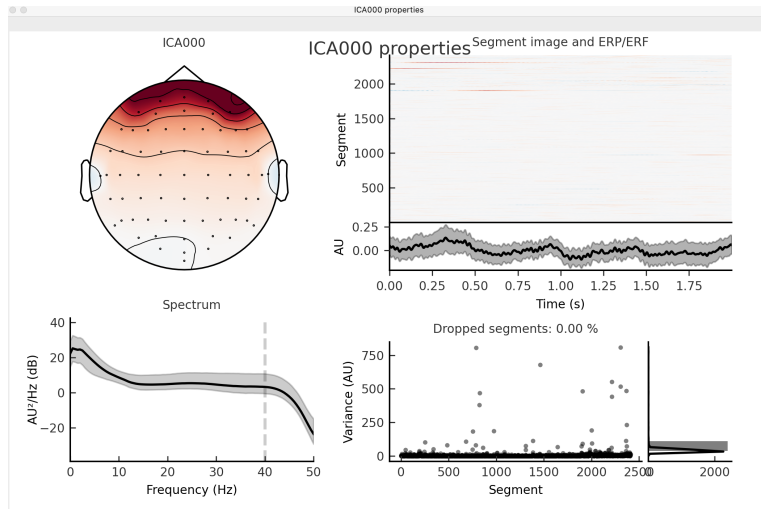


Figure 28: Independent component representing blink eyes, viewed topologically, there is strong symmetrical frontal activation.

A second component easy to recognize is disturbance due to eye movement. The eyes behave like large dipoles due to high metabolic activity.

On the spatial representation, there will be a one-sided polarization/depolarization [60].

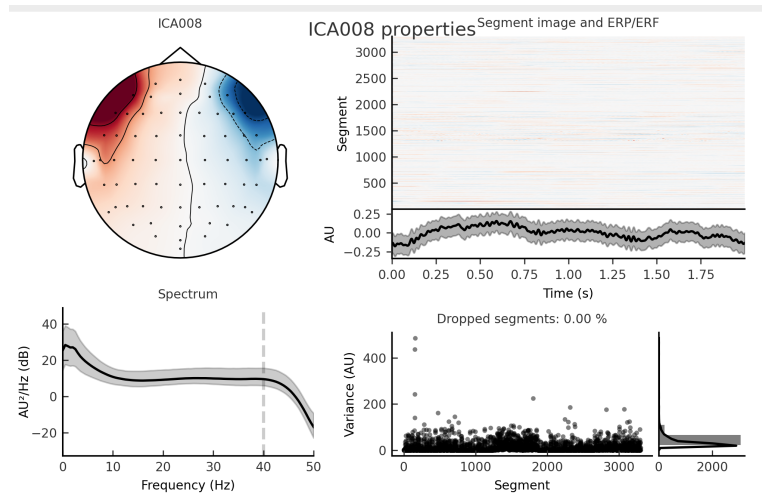


Figure 29: Usual eyes shifting independent component representation on topomap.

The strategy with less recognizable components is conservative. Because the deletion of components is decreasing the variance, i.e. information, we must be careful to keep as much as possible. The risk is to remove components containing the useful signal.

3.10.3 Epoching

The data from the listening trials fig. 26 (7) are aggregated together, forming an epoch emphasizing the useful signal from the trials by removing non phase locked signal.

There are 16 trials per tempo, yielding a total of 48 trials fig. 15. The initial recording frequency of 1024 Hz is decimated by 4 leading the epoch frequency to 256 Hz. A low pass filter with a cutoff at 64 Hz is applied. And a high pass with cutoff frequency at 0.1 Hz (Chebyshev 5th order) is applied.

The data is also re-referenced to the average of mastoids channels; bad channels are interpolated and data are filtered via the application of the ICA matrix. Once the preprocessing is finished, the data are saved as an epoch.

3.11 Rejecting epoch

The rejecting step fig. 26 (7.5) is a manual step of checking the obtained epochs and rejecting an epoch if it is significantly corrupted by artifacts.

3.12 Transformation of data

The data are then recorded fig. 26 (8), as a cycle to analyze the EEG response during the cycle of a single pattern.

The data are recorded in the frequency domain using direct Fourier transformation

implemented with an FFT.

The data are averaged before the FFT transform, in the time domain before and it is also possible to apply a kernel-based filter fig. 11 in the frequency domain to remove noise and the general trend (10).

The kernel removes the average value of the neighbors of the frequency of interest, fig. 11 allowing to override the frequency trends.

3.13 Perspectives for preprocessing

The preprocessing is a crucial step and must be done carefully before any analysis, the quality of the analysis depends indeed on the quality of the data, this concerns temporal and spatial filtering techniques, detrending, regression, rereferencing of rejection corrupted data, spatial interpolation [61].

As explained previously fig. 10, the EEG is so sensitive that even with optimal conditions the data are not be perfectly clean, the useful signal is never isolated, even by imagining removing all the classic noise, noise from other brain processes is always captured in the same way as the useful signal (2.3.1).

The preprocessing can be done in several different ways to clean and correct the data, it goes through a rejection of the data which are bad, by the selection of the most interesting electrodes, by the installation of filters eliminating the useless frequencies for our application and by simple decimation to lighten facilitating the calculations.

More complex preprocessing processes used to analyze (sometimes in a semi-parametric or non-parametric or data-driven way) the data and to maximize and minimize certain aspects through filters.

We therefore use decomposition of our signal via [principal component analysis \(PCA\)](#) or ICA but it is also possible to use more suited filters and adapted to emphasize or attenuate certain more precise aspects of acquisitions (to remove some artifacts).

Others methods exists and will be considered in a more advanced version of the developed analysis pipeline, for example [multiway canonical correlation analysis \(MCCA\)](#) [62] [63], to exploit the consistency of the spatial distribution between participants to combine optimally EEG records, [sparse time artifact removal \(STAR\)](#) to remove and repair rare artifacts on channel without inducing other perturbations [58] [64], or [rhythmic entertainment source separation \(RESS\)](#) to select precisely region of interest related to steady state processes as used in this experiment [58].

3.14 Group level analysis

The next step describe analysis performed after grouping the previous data. This time the analysis is done at the whole participant level allowing an analysis of the trends concerning the different features (behavioral analysis of the beat, temporal-frequency analysis stratified by tempo) to answer to the research question (4).

The statistical analysis is performed with python numpy, scipy and datamodels. Significance level is set to $P < 0.05$.

Numerical values are compared using T-test, analyse of variance (ANOVA) models or Kruskal-Wallis non parametric Test.

Categorical values are tested with khi square and McNemar test.

Pearson's Correlation are used to test linear correlations.

Holm-Bonferroni and Greenhouse-Geisser (for ANOVA) corrections are applied for repeated measurements on same data.

3.15 Tapping analysis

For each participant, it is interesting to analyze the frequency of tapping. This can be represented by several ways, the idea is to understand and compare the frequency, the periodicity, the tapping precision, if the tapping is synchronous with the audio stimulus, and then to classify data by tempo and compare these different classes.

Two ways of quantifying the taps are used in the presented experiment, the first method (3.15) analyze the tap timing of the participant in relation to the audio sequence played timing.

The second representation is interested in the times between two taps, giving an idea of the intervals between two successive taps and therefore of the tapping period.

The taps over time It is possible to find the number of taps per pattern cycle by performing a modulo operation.

To know if the theoretical tap model is fitting well, it is possible to perform the modulo operation using another period.

These alternating periods are chosen with respect to a period corresponding to a harmonic of this base period (pattern cycle period), sticking with one of the theoretical models stated:

1. The participant taps twice per cycle, so a tap every 6 elements (the pattern cycle being composed of 12 elements),
2. The participant taps 3 times per pattern cycle so a tap every 4 elements,
3. The participant taps 4 times per pattern cycle, so a tap every 3 elements,
4. If the participant taps 6 times per pattern cycle, so a tap every 2 elements.

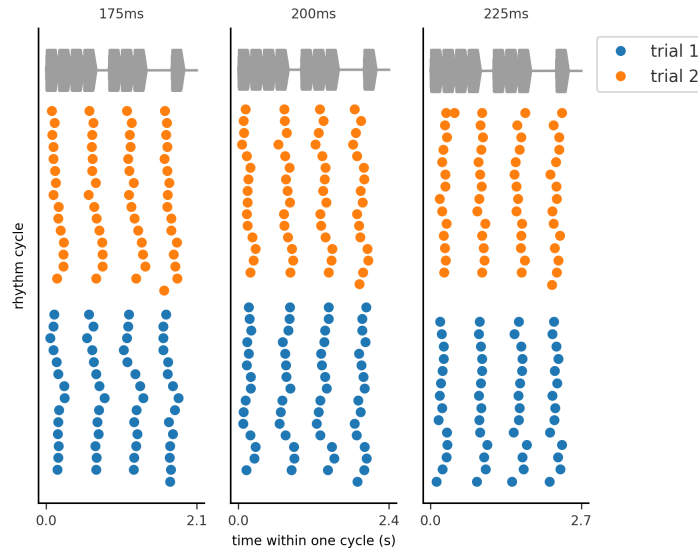


Figure 30: Usual representation of the taps for a participant, a visual inspection is very informative. X axis represents the relative duration of a cycle (in seconds), y axis represent the nth cycle (starting down until 17 cycle), the first start on the bottom, each trial have a different color. A perfect alignment in Y axis corresponds to a synchronous tapping with the cycle. A shift correspond to a progressive dephasing due to the accumulation of an error between tap and cycle, the participant isn't synchronized.

If the model does not fit, a progressive phase shift appears, because the modulo period does not correspond to a tapping period fig. 32.

The use of taps over time at each sub-periods is useful to look the quality of the tapping.

3.15.1 Time intervals between taps

An alternative way to represent taps is to look the time interval between two taps.

The information is summarized by picking the timing between taps, the inter tapping interval (ITI), it gives a relative measure of tapping. The theoretical tapping rhythm is 2 and 3 and 4 (6) taps per cycle (therefore the ITI have a period equal to 1/2, 1/3, 1/4 (1/6) of the cycle time).

The theoretical tapping periods are represented fig. 31 (if the person taps 2, 3, 4 or 6 times per pattern), it allows to show how the points are distributed.

If the participant is not tapping with an ITI corresponding to a integer subperiod of the pattern cycle (horizontal grey lines), the mean of ITI must stick to one of these subperiods fig. 31.

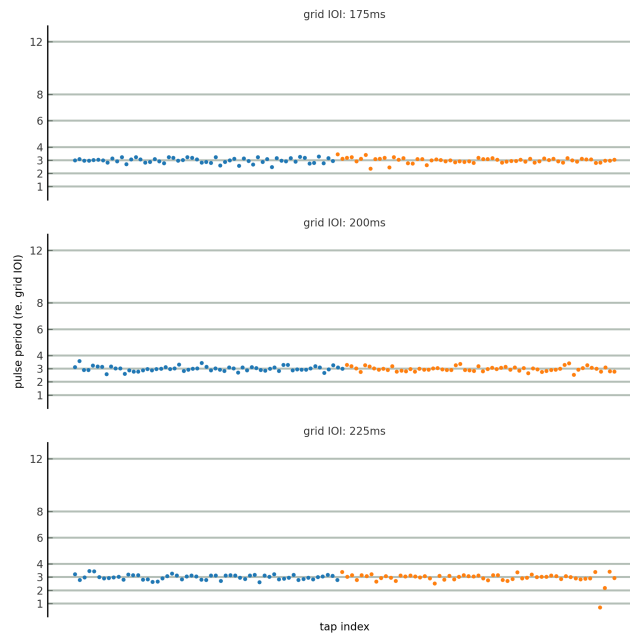


Figure 31: Representation at individual participant level of the **inter tapping interval (ITI)** for 3 tempi (top: fast, middle: medium, bottom: slow tempo). X axis represent ITI measure aligned in a linear way, Y axis represent ITI in second. Dash line represent theoretical tapping models, the ITI of the participant must be centered around one of this model to be phase locked. If the ITI is not centered his tapping is not going to be synchronized with pattern cycle, and his tapping is shifting over time.

The ITI is used to classify each trial than taps over time.

The values are sensitive to outliers (if the participant pauses, ITI is becoming very long), that's why it is necessary to remove these outliers beforehand.

The chosen method uses the quantiles and to systematically remove the extreme values, however the rejection of measurements is done by trading some statistical power.

A second problem with the ITI is that even if the mean (or median, more robust) value is close to a theoretical ITI, a gradual phase shift can occur.

We must stay careful, even if taps have a period close to a theoretical model, the taps are still sensitive to a systematic error inducing a shift in the tapping phase, this can't be visualized using ITI, that's why the taps over time are also explored to assess the quality of tapping (3.15).

This means that the tapping performed by the participant is not synchronous with the audio sequence presented.

To quantify this phenomenon various measurements exist, the solution remains to see the dispersion on the corresponding model using the taps times based on modulo operation over a subperiod and the tap time (3.15).

3.15.2 Classification

Before performing further analysis there is a need to classify the trials, the classes are representing the tapping profile, based on previous studies 4 classes are available, 2-3-4-6-tapper. The classification is based on the best fit between the median ITI from the tapping trial and the a theoretical (ITI) tapping profile:

$$TapperProfile \leftrightarrow \operatorname{argmin}(\operatorname{median}(ITI)_i - \theta_{tapModel})$$

With

$$\theta_{tapModel} \in \{\theta_{ITI-2}, \theta_{ITI-3}, \theta_{ITI-4}, \theta_{ITI-6}\}$$

The different classes are compared according to multiple Chi square tests in relation to the tempi.

This allows us to see if there is a variation between the distribution of the classes (of the tapping profiles) (H1) or if there is no modification in the distribution of the classes according to the tempo (H0).

3.15.3 Assess of the quality of tapping, error and bias

Even with a mean ITI close to an ideal theoretical average, there is no guarantee that the participant is synchronous with the audio stimulus, he may have a close ITI elicited rhythm but without being synchronized with the audio sequence.

If the participant is not synchronous with the audio sequence, the tapping is progressively dephasing, accumulating the error.

The question is to find an effective method to further subclassify participants as good or bad tappers in addition to their tapping frequency.

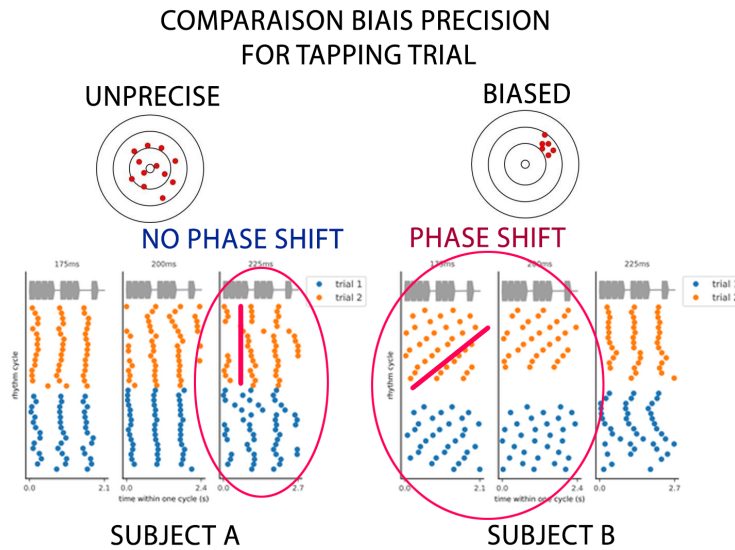


Figure 32: Comparison of two taps sequences from two different participants (left and right). On the left: a taps sequence from participant A, the taps trial is not very precise (left red circle), however there is no phase shift (red bar is vertical). Right: Participant's taps sequence with a systematic bias (red right circle) resulting to a shift (red bar is oblique) relative to the pattern cycle.

In fig. 32 two different behaviors of tapping are compared, participant A is imprecise but remains in phase, which does not lead to error accumulation and tapping shifting. On the other side, the participant is regular but the systematic bias induce a shift in his taps. The results of the second participant are biased, and therefore this participant does not tap according to the pattern cycle. He is qualified as a "bad tapper". Shift is therefore more important for tapper rejection than accuracy.

First approach: use the cumulative errors The first approach is to look at the cumulative errors by doing a cumulative sum of the ITI's.

The starting postulate: if the participant is synchronous with the sequence played, he is not accumulating a systematic error, the imprecision is therefore authorized, the bias (systematic error) is not, because it lead to a phase shift progressive.

A threshold is set when the cumulative error is too high.

The cumulative error is filtered before classification. The 10% quantile and the values greater than the 90% quantile are deleted, this is a radical method which has the disadvantage of deleting 20% of the available data and therefore of further reducing the power (reduced by the multiples classifications).

This method is not the most suited to find bad tappers as discussed (3.15.1).

Second approach: use the dispersion of the taps. A second method that can highlight a systematic tapping error (bias) leading to a phase shift is to use the taps times (and no longer the ITI), and to cycle this time in relation to the cycle period of the pattern or to one

of its sub-periods corresponding to the period linked to the tapping number. The cycle time is based on previous classification for each trial:

- if the participant is 2 tapper during his trial, the cycle will be half the period of the pattern.
- if the participant is 3 tapper during his trial, the cycle will be a third of the period of the pattern.
- if the participant is 4 tapper during his trial, the cycle will be a quarter of the period of the pattern
- if the participant is 6 tapper during his trial, the cycle will be the sixth of the period of the pattern.

In this way, if the participant taps in a regular way and is phase locked with the audio sequence presented, the phase remains stable. The position of the phase is not important, the most important is that it remains *stable* and phase locked.

This cyclic model once again makes possible to detect whether the tapping is stable and fits to a model [65].

This model assesses whether participants are synchronous with one of the theoretical tapping behaviors.

To obtain this representation, the entire tapping trial is cut using a modulo using one of the periods corresponding to the tapping behavior (corresponding to 1/2, 1/3, 1/4, 1/6 of the period of the pattern cycle therefore). Taps time after segmentation using a modulo corresponding to an entire subperiod of the pattern cycle are displayed in a polar way, where 2π radians corresponds to this subperiod.

If the tapping behavior (taps) is synchronous with the subperiod tested, the dots are supposed to be concentrated in one place fig. 30. The corresponding location's phase simply describes a delay between a point serving as a reference for the modulo operation and the moment when the person taps. This delay is therefore not important because the person can type whenever they wish.

The concentration of the dots (taps) in one place is more important, showing that the person is in sync with the ideal tapping period tested (2, 3, 4, 6 tapping). If dots are localized in an unique phase, the participant is tapping at regular intervals and staying in phase.

If the participant is no longer in phase lock with the pattern cycle, the participant is gradually shifting out of phase, resulting in a dispersion of points on the circular graph.

The subperiod used for the modulo operation correspond to the best fitting theoretical ITI period between median ITI of taps and this theoretical ITI (corresponding to 1/2, 1/3, 1/4, 1/6 of the period of the pattern cycle), a classification is done before testing the accuracy and the validity of tapping trial.

The general Mean vector length (red bar) represents this tendency: the more the points are concentrated, the greater this norm is, if the points, on the contrary, are dispersed through

the cycle, the general norm is be close to zero, reflecting an inconsistency in the synchronization.

If the participant has a different tapping behavior from the tested model, the tapping goes out of phase, general mean vector length will be small and the tapping trial will be qualified as bad.

This model is suited for:

- Identify the accuracy of the tapper, and see if he is synchronous with a theoretical tapping period and expresses this with a strength,
- Identify bad tappers using threshold on general mean vector length or using statistical test as Rayleigh test.

To statistically test this taps dispersion on the circle, a *Rayleigh* test is performed, This test detect if a cyclic distribution is *uniform* by performing the uniformity test, P values are corrected using Holme Bonferroni method.

One of the drawbacks of this cyclic method is due to a possible overlapping in models, between the 2-tapper, 4-tapper and 6-tapper model, an overlap between the 3-tapper and 6-tapper models also exists. This is illustrated by looking how all models fit to a participant fig. 39

Before looking at the precision and the fit to a model, it is therefore necessary to look at the trend and not to use this method as a tapper classifier because the model has a high sensitivity (it detects well the fitting to a model) but is not very specific (taps can fits to several models).

Bad tappers classification Based on previously specified metrics a classification between good tappers and bad tappers is done. The heuristic chosen is based on the shifting of taps during the tapping trial, using previously described circular technique, and using the general mean vector length. If the general mean vector length is too small, the trial is classified as bad, if it is high enough, the trial is classified as good.

The distribution of good and bad tappers across tempi is also explored:

-H0: There is no demonstrable relationship between tapping quality and tempo

-H1 there is a statistically significant relationship between tapping quality and tempo

A chi square test is performed to assess these hypothesis.

Classification accuracy Finally the previously described method using the general mean vector length is compared to a manual classification.

This ensures the validity of the method and allows to some extent to quantify the quality.

Accuracy and precision are assessed using a contingency table.

Macnemar test could be relevant to evaluate a potential difference between manual classification and the classification based on the shift.

3.16 Time visualization

The temporal aspect of the EEG response is not analyzed in depth, however certain aspects are visualized in order to ensure that there is indeed a general EEG response during the presentation of the audio stimulus.

The frequency tagging method allows us to perform more efficient and easier analyzes in the frequency domain.

3.17 Frequency analysis

Analyzes in the frequency domain focus on the variation (or not) of features related to the spectrum according to the tempo.

For each participant, the signal is cut into 16 epochs by tempo bloc, these epochs are then averaged.

This time domain averaging greatly increase the SNR by eliminating the activity which is not phase locked with the stimulus across the trials and considered here as noise.

The averaged waveform is then transformed into the spectral domain via a **discrete Fourier transformation (DFT)** implemented via **fast Fourier transformation (FFT)** algorithm.

The spectrum is normalized by filtering the frequencies of interest by removing the average magnitudes from distant neighbors (-5 to -2, and +2 to 5 neighbors) of the frequency of interest (applied as a sliding window along the spectrum) fig. 10.

Frequencies of interest These interest frequencies fig. 52 studied are related to stimulus pattern cycle periods composing the trial. There are 3 different tempi depending on the duration of the elements composing the pattern cycle composing the sequence:

- 175 ms per element, for a total duration of 2.1 Second of cycle, therefore the fundamental and the harmonics at 0.476 Hz, 0.952Hz; 1.43Hz , 1.90Hz 2338Hz, 2.86Hz,...
- 200 ms per element, for a total duration of 2.4 Second cycle, Spectrum harmonic related with a fundamental at 0.417Hz and harmonics at 0.833Hz, 1.25Hz, 1.66Hz, 2.08Hz,...
- 225 ms per element, for a total duration of 2.7 Second cycle, Spectrum harmonic related with a fundamental at 0.37 and harmonics at 0.74Hz, 1.11Hz, 1.48Hz, 1.85Hz,...

These 12 frequencies of interest encompass the frequency of presentation of the stimulus up to the frequency corresponding to the presentation of an (former) element (worth 1/12 of the period of the cycle), this is why the analysis focuses on these 12 frequencies. This is based on a one-to-one mapping between the envelope of the rhythmic input and the EEG output hypothesis [10].

The magnitude of the EEG response is evaluated on 12 frequencies corresponding to the fundamental and to 11 harmonics of the pattern cycle's period representing the EEG response to the envelope frequencies, the study focus on these 12 frequencies coming from

audio input, the higher frequency is linked with the former element period. The frequency analysis is done at these points of interest corresponding to the modulation of frequencies of the EEG response to the input presented.

SNR Visualization As a preliminary analysis, the signal at the frequencies of interest is compared to the signal outside these frequencies considered as non-informative signal for the application, considered as noise.

Standard deviation visualization Before studying the acquired spectrum in depth, it is also interesting to visualize the standard deviation of the signal, specifically at the frequencies of interest giving an idea of the variability of the data and the plurality of profiles acquired.

3.17.1 Overall gain

The first analysis study the total amplitude at the frequencies of interest and of the variation of this amplitude according to the tempo.

For this a simple ANOVA is used and allows to know if there is a variation of the total amplitude between the tempi (H1) or if on the contrary this amplitude and therefore this energy elicited by the EEG response is invariant (H0).

3.17.2 Input output analysis

The input - output comparison compares in a pairwise way features between the spectrum from the input sequence and between the spectrum from the EEG response.

This kind of comparison is important to assess if the brain is reacting (or not) to the input stimulus, if the frequency response are (or not) at same position in the spectrum and if there is (or not) a non linear transformation between input amplitudes [66] and output amplitudes in the spectrum [23].

A null hypothesis (H0) is a EEG response just following passively the input signal.

The alternative hypothesis (H1) is a transformed EEG response to the input signal.

Multiple one way t-tests are done to compare each interest frequencies between input and EEG response (output) spectrum.

3.17.3 Scalp distribution

The scalp distribution of energy is interesting, many analysis use only a subset of electrodes where the activity is higher on the scalp.

The amplitude of each frequencies of interest are plotted for each electrodes, electrodes in the area where the activity is higher should be used for further analysis. This define our region of interest (ROI).

3.17.4 Meter related frequencies

Some frequencies associated to the perception of the meter by the participant are supposed to be enhanced [67].

By using the results of the tapping trial, a majority group of tappers emerges, in general people tap 3 times per pattern cycle.

We assume that tapping is directly related to the perception of meter and beat [14].

And relying on the hypothesis of the enhancement of meters related frequencies [67].

The study will therefore focus on the study of meters related frequencies corresponding to the profile of this majority tappers group (3-tapper) corresponding to the general perception of the meter.

The frequencies related to a 3 meter perception are the frequencies corresponding to the subperiods of the pattern cycle, therefore the frequencies corresponding to the third of the period of the pattern cycle and to multiples of this first subperiod (corresponding to the harmonics).

Z score using meter related frequencies Analysis harmonic by harmonic is laborious and increases the complexity of the analyses.

To resolve this problem, a Z score is used comparing all harmonics with a subset of harmonics according to the meter perception. The method to objectify a potential effect or to be able to compare different conditions is to use a Z score between the meter related frequencies and the harmonics.

This Z score is calculated from the samples recorded on a subset of 9 channels (the fronto-central group). The spectral response is obtained via an FFT and the magnitudes between the channels are averaged.

The Z score used in these analysis are calculated on the 3-meters related frequencies compared to the whole set of interest frequencies because the tapping trial has shown a majority of 3-tappers.

The magnitudes at all frequencies of interest are computed, (i.e. at the harmonic frequencies corresponding to the period of the cycle according to the tempo). The magnitude of meter related, and meter unrelated frequencies are also computed.

From there it is possible to calculate the Z score, $Z_i = \frac{\mu_m}{\sigma_m}$ with the average between the amplitudes $\mu_m = \frac{\sum_i^N m_i}{N}$ and the variance $\sigma_m = \frac{1}{M} \sum_i^N (m_i - \mu_m)^2$.

The Z scores for each 3 meters related frequencies are then averaged to obtain a final score:

$$Z_{meterRelated} = mean(\{Z_{freqRelated1}, Z_{freqRelated2}, \dots, Z_{freqRelatedN}\})$$

The 3-meters related frequencies Z score is the average of the Z score of each 3-meters related frequencies.

Comparison of 3-meters Z score between input and output (EEG response) The 3-meters Z score are calculated for the input signal spectrum and for the EEG response

spectrum, Z scores are compared using one sample T-test for each tempo.

Comparison of 3-meters Z score across tempi The last statistical analysis compares the Z score of each participant between the 3 tempi.

The goal is to see if there is a change in Z score between tempi. A change in Z score would mean a fluctuation in the perception of 3-meters related frequencies between tempi (H1). If no change is seen between tempos, this could suggest an invariance in the EEG response (H0).

For this an ANOVA is performed comparing the 3-meter Z scores of each participant between the tempi.

4 Results

4.1 Participants data

We collected data from a sample of 12 healthy participants. One participant was discarded due to a technical issue during the experiment. The average age of the participants is 22.23 years, with a standard deviation of 1.47 years.

There are 7 males and 6 females. 4 out of 13 participants have a musical background (> medium level⁶) and 4 participants have a dance-related activity (> medium level), the profiles are diversified.

The study has been approved by the local Ethics Committee and is conducted at the Catholic University of Louvain (UCLouvain) in the [institute of Neurosciences \(IONS\)](#).

Participants are informed of the purpose of the study and the process of the experiment [fig. 15](#). They signed an informed consent form agreeing to auditory stimulation, extracranial scalp [electroencephalogram \(EEG\)](#) recording and a behavioral tapping test.

All the participants included in the experiment met the inclusion criteria ([6.1](#) [4.1](#)), they had no history of psychiatric disorders, neurological diseases, history of epilepsy, hearing disorders.

Inclusion criteria:

- The participant has no known psychiatric, neurological or history of epilepsy,
- Participant has no hearing impairment,
- The participant is not under psychoactive medical treatment, he is not under the influence of other psychoactive substances during the experiment,
- Participant morphology allows data acquisition via EEG,
- The participant is naive to the procedure, it is his first frequency tagging experiment studying the rhythm.

The place and the conditions were rigorously controlled and did not change for all the acquisitions of the cohort.

Below is the summary table of the data relating to the participants fulfilling the inclusion criteria and whose EEG and tapping (behavioral) data collected are analyzed ([4.1](#)).

⁶More than 3 years and/or regular practice.

Information about participant							
Nb	Age	Sex	Hand	Musical Experience	Dancing experience	Status	Exp
1	24	M	R	Small	No	Student	OK
2	19	F	R	Small	Small	Student	OK
3	24	M	R	Medium	No	Student	OK
4	22	M	L	Serious	No	Student	OK
5	24	M	R	Small	No	Student	OK
6	22	F	L	Small	Serious	Student	NOK
7	22	F	R	Small	No	Student	OK
8	22	M	R	No	No	Student	OK
9	21	F	R	Small	No	Student	OK
10	24	F	R	Medium	Medium	Student	OK
11	21	M	L	Small	No	Student	OK
12	21	M	R	Small	Medium	Student	OK
13	23	F	R	Serious	Medium	Student	OK

Table 2: Participants information.

4.2 Tapping analysis

The behavioral experimental task explores the participant's perception to the rhythm meter and beat elicited by the audio stimulus sequence.

The participant is supposed to listen and try to detect a general and constant meter in the presented rhythm, next he is supposed to express it by tapping at regular intervals on the tapping box.

4.2.1 Measure inter-tap intervals

For the fast tempo: a mean **inter tapping interval (ITI)** of 0.85 sec (std. 0.37 sec), with an ITI variation coefficient of 6.4 % (std. 4.3 %) and an model fit coefficient of variation of 6.7 %⁷

For the medium tempo: a mean inter-tap interval of 0.93 sec (std 0.26 sec), with an ITI variation coefficient of 6.4 % (std. 2.8 %) and a model fit coefficient of variation of 6.6 % (std. 3.6 %).

For the slow tempo: a mean inter-tap interval of 0.99 sec (std. 0.25 sec), with an ITI variation coefficient of 5.8 % (std. 1.8 %) and a model fit coefficient of variation of 5.8 % (std. 1.6 %).

There is no statistical difference of the variation coefficient using **analyse of variance (ANOVA)** ($F = 0.25$, $P > 0.75$, $df=2$) and model fit coefficient of variation using ANOVA ($F = 0.49$, $P > 0.61$, $df=2$), the best P value reported with post hoc test is $P > 0.47$.

The variability is stable for the two slowest tempos and increases for the fastest tempo.

4.2.2 Difference in the tapping period between the 3 tempi

It is possible to check if there is a significant difference between the averages of the measures of ITI periods for each tempo **3.15.1**.

For this an ANOVA is made.

It shows a statistically significant difference ($F=63$, $P<0.01$, Degree of freedom =2) between the average values of ITI between the 3 tempi.

The analysis verify that the behavioral task is indeed influenced by the input audio sequence.

Post-hoc tests are carried out, confirming and detailing the results.

⁷The coefficient of variation correspond to the standard deviation divided by the ITI mean or an ITI from a corresponding model which fit the best, it is a simple measure of accuracy **[68] [69] [70] (3.15.1)** % (std. 4.9 %).

This coefficient can be calculated on the value of the theoretical intertap timing of the best fitting model to the participant (for example if the participant have a tapping behavior of 3, (resp 2, 4, 6) tapper (tap per pattern cycle), the theoretical ITI is the pattern cycle time divided by three (resp. two, four, six).

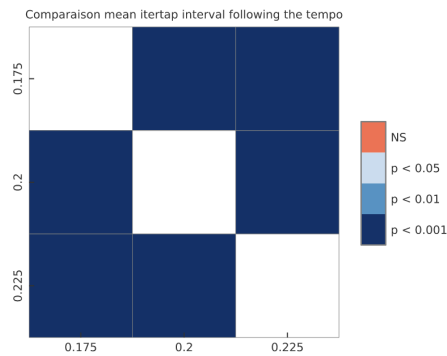


Figure 33: Matrix showing the significance level from pairwise T-test from post hoc test comparing tapping period value at 3 tempi.

Statistical analysis on mean inter-tap interval is less relevant because many tapping profiles coexist for each tempo (2-3-4-6 tappers) fig. 34. Experimental data often corroborate to these theoretical models at participant level, at a global level, a polymodal distribution model emerge, fitting to these models fig. 34.

4.2.3 Representation of ITI for each tempo

The ITI from each trials are represented.

Histogram inter tapping times

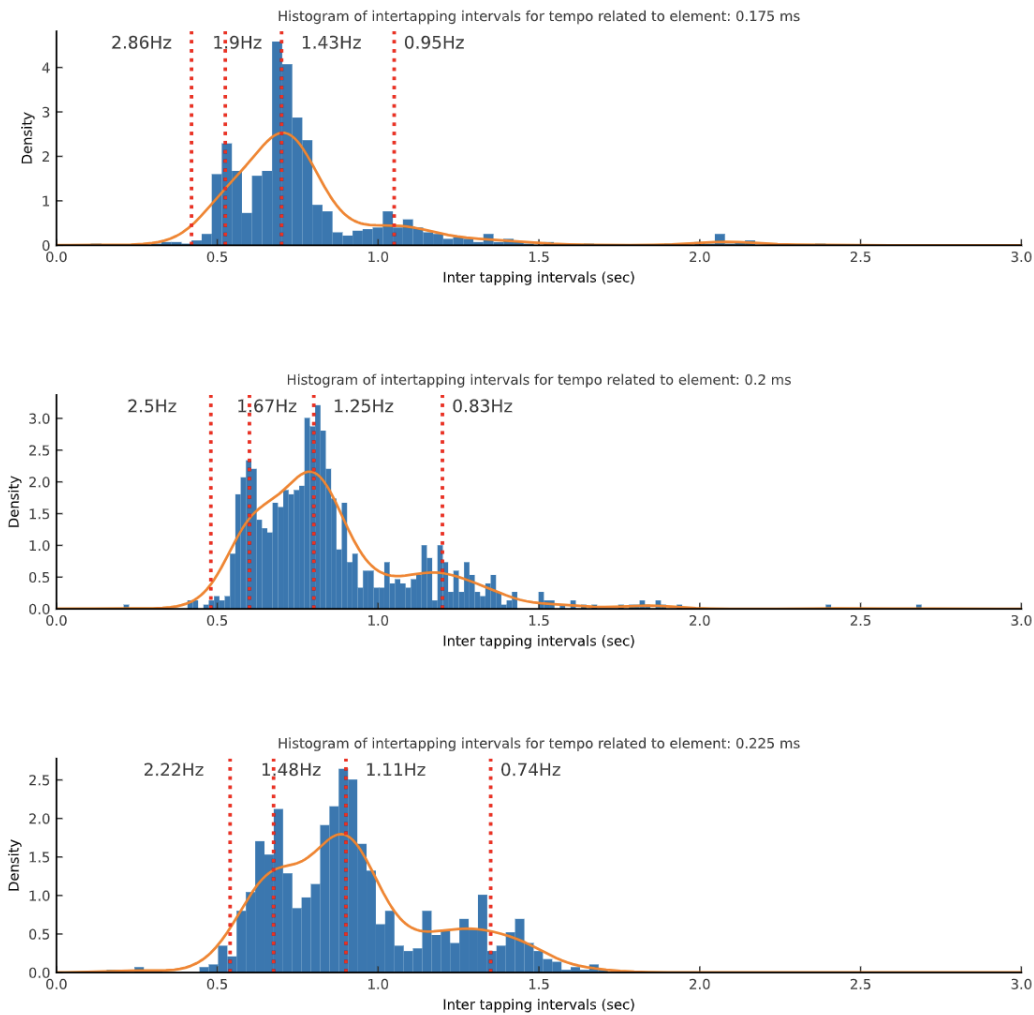


Figure 34: Representation of all ITI across all participants classified by tempo (top: fast, middle: medium, bottom: slow tempo). The distributions exhibit several local maxima indicating a multimodal distribution. These local maxima are aligned to the ITI corresponding to the theoretical tapping periods (2, 3, 4, 8 tapper).

The representation using a histogram with the densities shows that the distribution is not following a normal distribution [71].

Several peaks are present during the distribution suggest a multimodal type distribution (3-modal).

these peaks correspond to the corresponding ITI respectively:

1. At the period of the pattern cycle divided by 2, i.e. 2 taps per pattern cycle,

2. At the period of the pattern cycle divided by 3, i.e. 3 taps per pattern cycle,
3. At the period of the pattern cycle divided by 4, i.e. 4 taps per pattern cycle.

It is therefore necessary to take care of the subtypes of tappers in the analysis. A classification is made.

fig. 34 shows this distribution, the different local maxima suggest that the studied sample is composed of different profiles of tappers, in accordance with theoretical models [11]. The most prominent trend, however, is during the tapping period corresponding to a 3 tapper behavior. This agrees with previous studies [10] showing same results for similar tempo, the tendency of ITI is around 600-800ms per tap (corresponding to a 3 tapper for a cycle period between 2.1sec to 2.7sec).

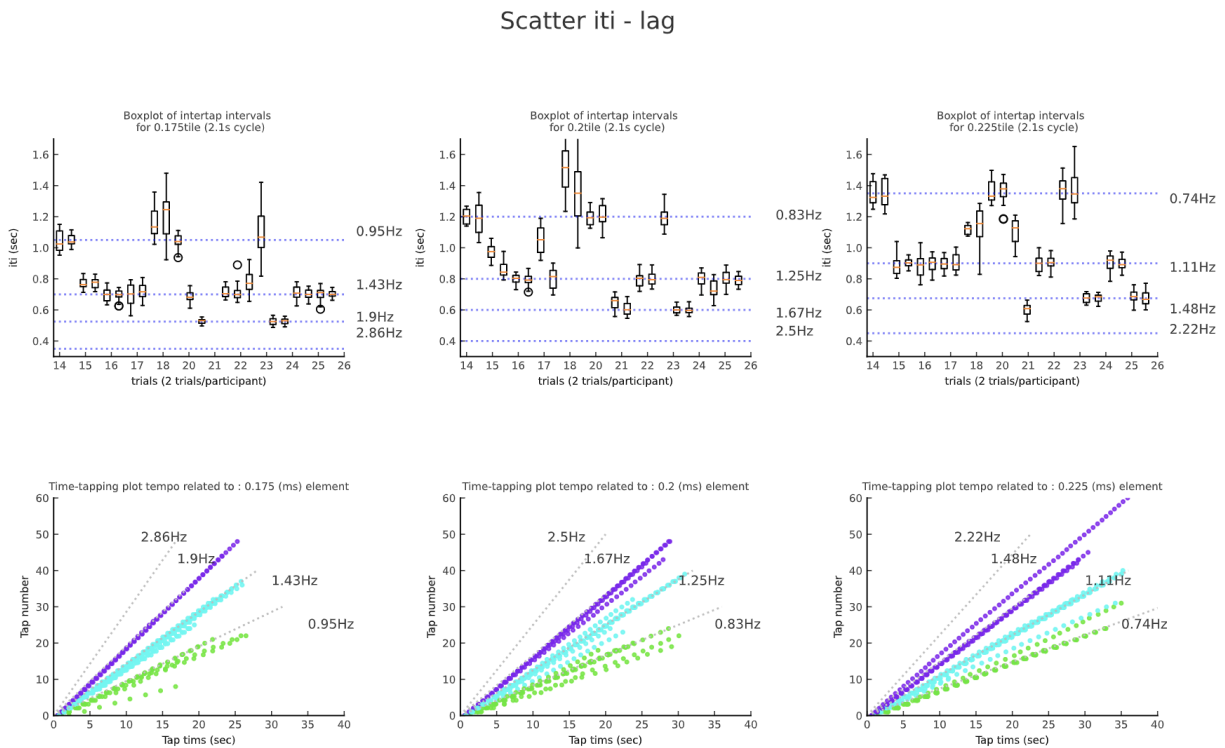


Figure 35: Top: The diagram represents the average, the percentiles and the outliers of the values of the ITI periods during the tapping trial, the horizontal bars represent the intervals expected according to the theoretical tapping periods. The results are compared to the 3 tempi. The results between two bars are bad trials (the tapping period doesn't correspond to an entire subperiod of the pattern cycle), or no tapping synchronous with the cycle was found, which cause a phase shift and a tapping unrelated to the sequence presented. Bottom: relation between taps and time. Each color represent a tapping profile class, in purple: 4 tappers, cyan: 3 tappers, green: 2 tappers. Left column is fast tempo (175ms), middle column is the medium tempo (200ms), and right column corresponds to trials at slow tempo (225ms). Grey dashed lines correspond to theoretical tappers profile and the taps frequency corresponding.

Classification The classification [3.15.2](#) is done by comparing the goodness of fit between the theoretical models and the ITI data filtered by the quantile method (10 - 90 %), the profile of tapper is done according to the associated model that fit the most fig. [\(3.15.2\)](#).

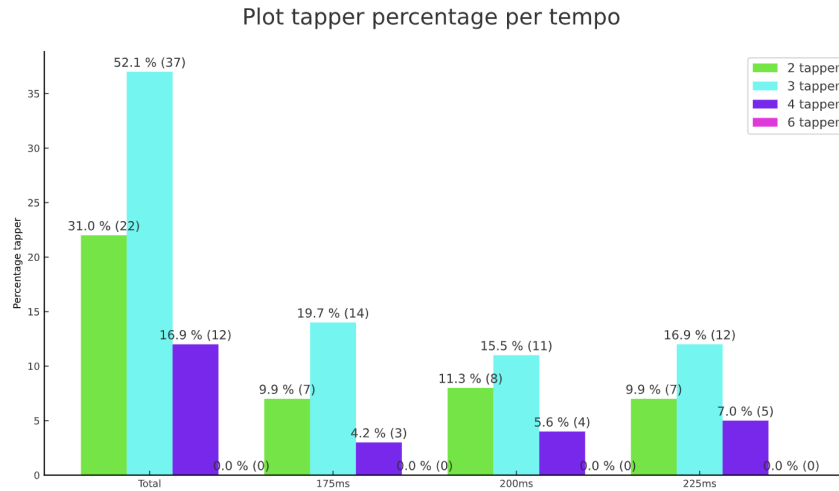


Figure 36: On the left: global distribution of taps. Second: distribution of taps in the fast tempo class. Third: distribution of taps in the middle tempo class. Right: distribution of taps in the slow tempo class.

The trend of taps by pattern cycle by tempo is displayed fig. [36](#), there is no 6 tapper. Subdivision by tempo shows no influence of tempi on the tapping behavior of tappers. A chi square test on the contingency table, grouping the profiles of tappers and by tempi also shows no trend ($P = 0.91$, degree of freedom = 4) according to a statistic from Pearson's chi-squared. The predicted frequencies in the event of non-correlation between the variables (H_0) are close to the frequencies of the observations obtained.

Quality of tapping, error and Bias The first approach [\(3.15.3\)](#) using a cumulative error using the difference between the trial ITI and the best-tapper fitting model ITI (based on previous classification).

Cumulated error over time

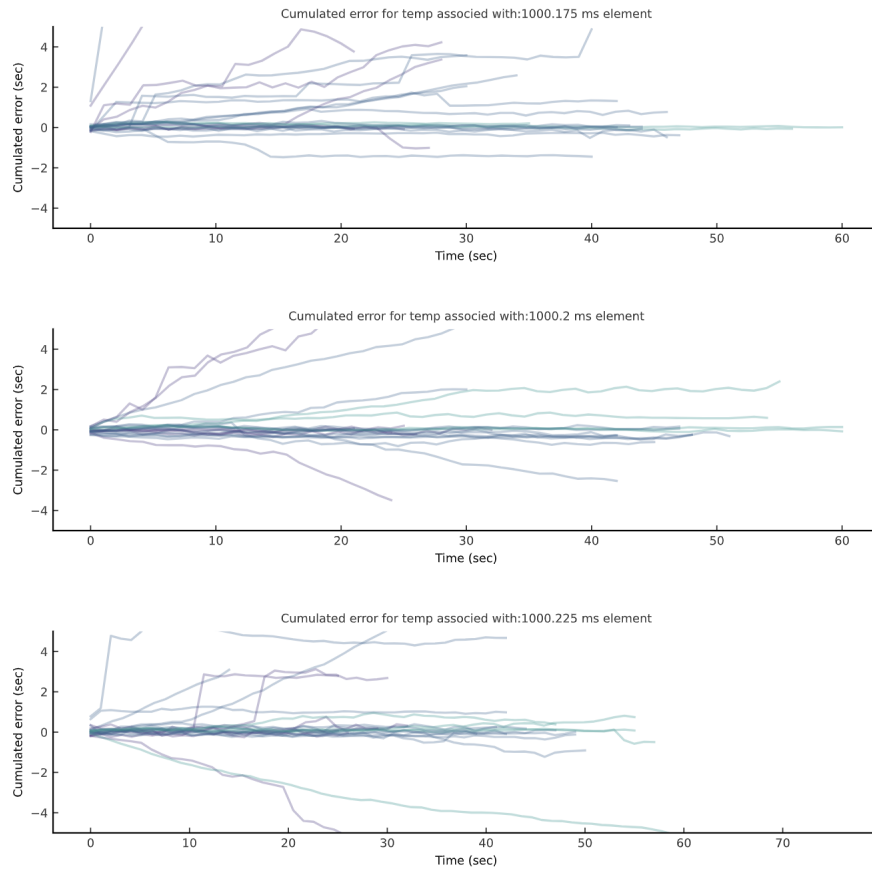


Figure 37: Representation of error accumulation in time without outlier rejection. Y axis: time scale in second, representing the shift in time from the ideal tap interval. X axis: tap sequence. Each line represents a taps trial.

The plotting of the cumulative error, the values are centered in relation to the theoretical tap time which fitted the best.

Tapping error behaviors are visualized as slow drift but there is also the presence of jumps. This is an error induced when the participant stops tapping, thus highly modifying an ITI, an ITI is punctually increased.

The solution is to filter the ITI data, which avoids this kind of problem and keeps only the systematic errors.

Cumulated error over time

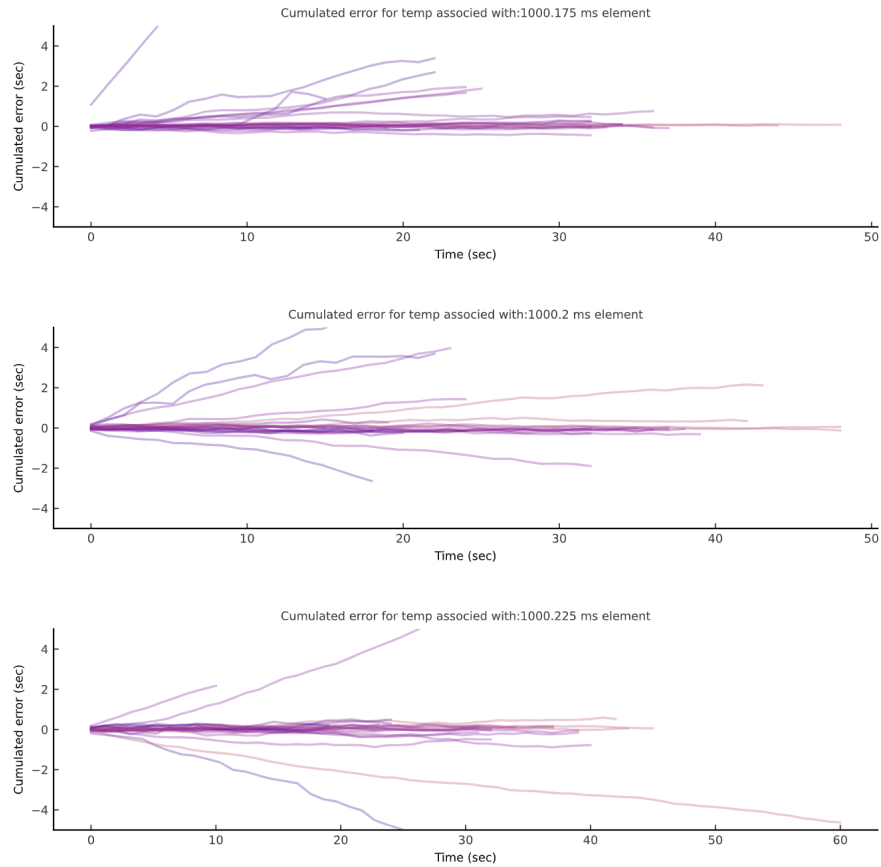


Figure 38: Representation of error accumulation in time after outlier rejection. Y axis: time scale in second, representing the shift in time from the ideal tapping interval. X axis: tap sequence. The presence of step is removed on the graph.

The filtered data allows to see the progressive phase shift behavior of the tapping during certain events.

A more accurate and suited method to assess the quality of the tapping rely on the shift of taps during the tapping trials (4.2.3).

Cyclic representation of dephasing For each participant a cyclic representation of the taps can be represented,

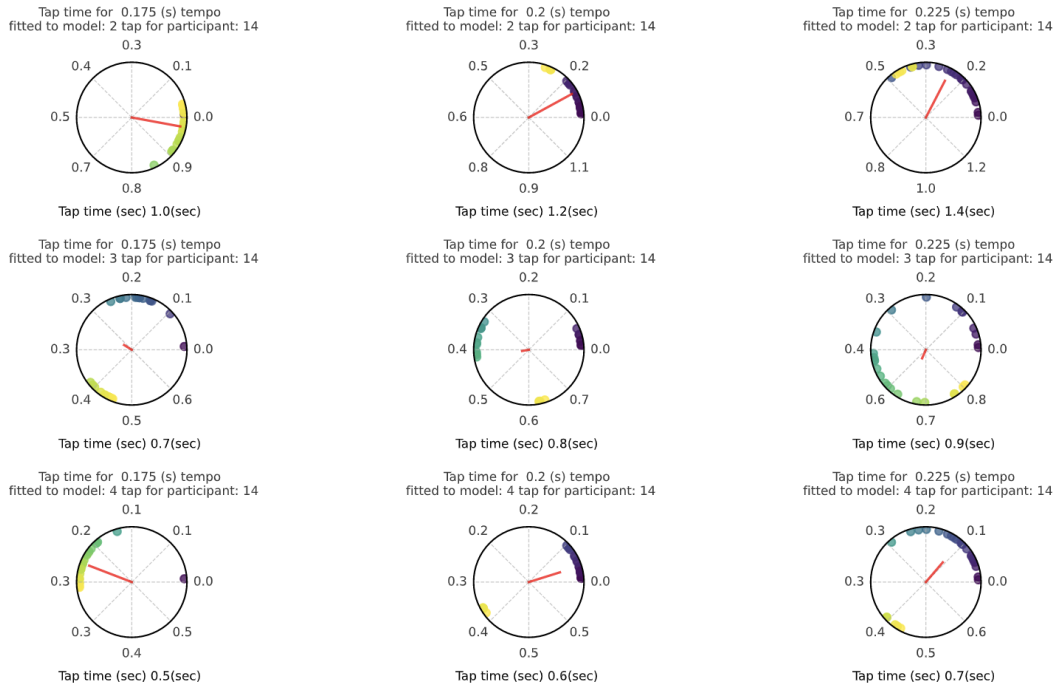


Figure 39: Circular representation subset. Each circle represents the data distributed and scaled according to a tapping model (2-3-4-6 tap per pattern cycle), the perimeter represents the ideal tapping period (Pattern duration/(2-3-4-6)). The points no longer represent the ITI but the tapping time in a window corresponding to the ideal theoretical period. The general trend is summarized by a mean vector length (red bar) representing the strength of the phase precision, the phase represents the lag between the start of the window and the moment when the person taps.

For example on the fig. 39 there is an overlapping between fit with model 2 tapper and model 4 tapper for the fast tempo for participant 14.

That is why this model is not used for classification but to assess the accuracy of the tapping, and is used in bad/good tappers classification (3.15.3).

This circular representation represent the phase locking of taps during the tapping trial.

TAPS REPARTITION FOR PARTICIPANT 22 SLOW TEMPO

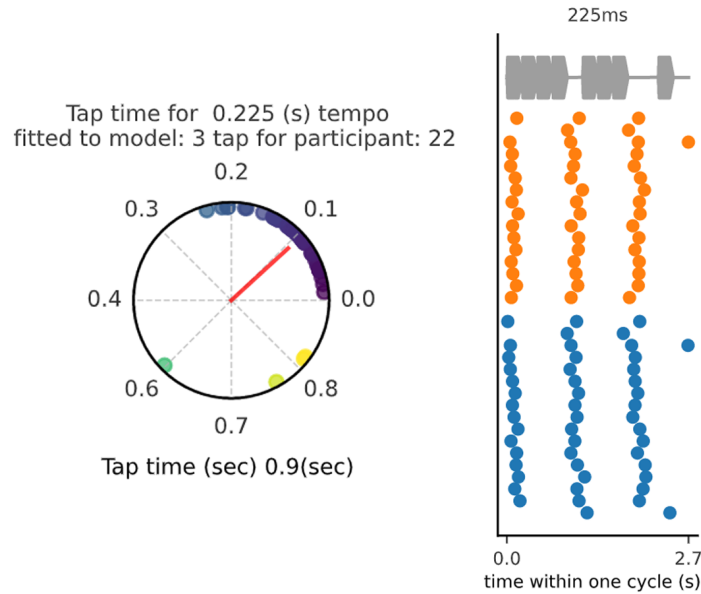


Figure 40: Illustration of a tapping trial at slow tempo (225ms), Right his taps are stable across the trial and stable following the pattern (phase locked) cycle period, he is tapping 3 times per pattern cycle period, he is classified as a 3 tapper. Left: the circular representation fits taps a 3 tapper model, the circle represents the pattern cycle divided by 3, and taps are represented following this same metric. Scatter are focus in an area. The Mean vector length (red bar) represents this trend.

On the fig. 40 a tapping trial is represented, taps are represented (right) following a pattern cycle period. The tapper is classified by argmin method (3.15.2) as a 3-tapper, circular representation (Left) fit tap time on a 3-taps period (pattern cycle period divided by three). The concentration of points are represented by the mean vector length (red bar), this red bar is high, so the participant 22 is qualified as a good tapper for this trial because he is synchronous with the pattern cycle.

TAPS REPARTITION FOR PARTICIPANT 15 MEDIUMTEMPO

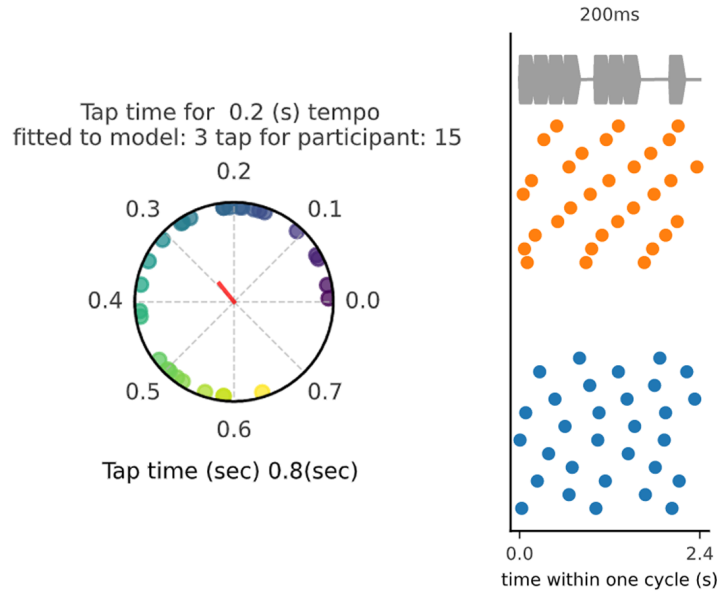


Figure 41: Illustration of a tapping trial at medium tempo (200ms), Right his taps are varying across the trial and not stable following the pattern cycle period, he is tapping 3 times per pattern cycle period, he is classified as a 3 tapper. Left: the circular representation fits taps a 3 tapper model, the circle represents the pattern cycle divided by 3, and taps are represented following this same metric. Scatter are not focus in an area. The mean vector length (red bar) represents this trend.

On the other hand On the fig. 41 a tapping trial is represented, taps are represented (right) following a pattern cycle period. The tapper is classified by argmin method (3.15.2) as a 3-tapper, circular representation (Left) fit tap time on a 3-taps period (pattern cycle period divided by three). The concentration of points are represented by the mean vector length (red bar), this red bar is low, so the participant is qualified as a bad tapper for this trial because he is not synchronous with the pattern cycle.

Participant are classified using this method, tapper-profile classification, and next prominence of mean vector length to assess the quality of the tapping.

4.2.4 Classification and error set

Based on these previous criteria it is possible to classify synchronous tappers as good tappers, and non-synchronous tappers as bad tappers (3.15.3).

Histogram after classification

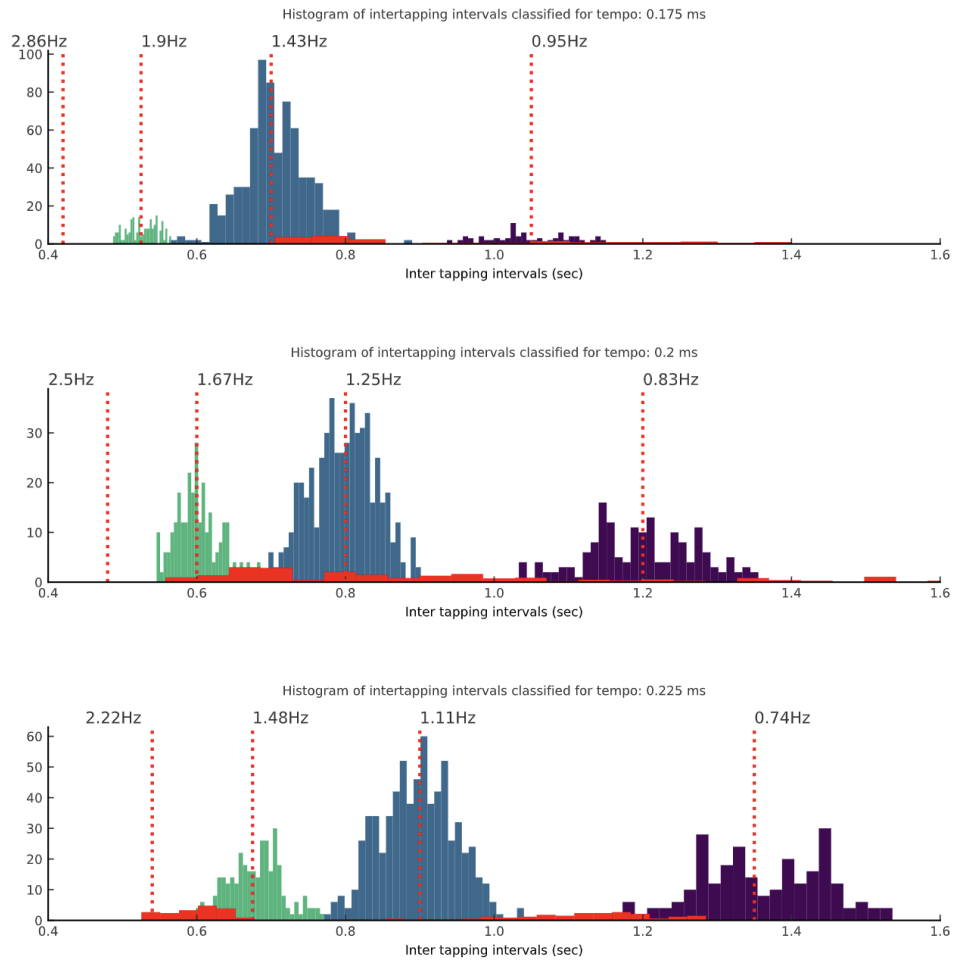


Figure 42: Distribution of the sample represented as a histogram. In green: distribution of trials corresponding to a behavior of 4 tapper. In blue: representation of the trials corresponding to a behavior of 3 tapper. In purple: distribution of the sample corresponding to a behavior of 2 tapper. In red: trials classified as bad tapper, not corresponding to any plausible model.

Bad tappers are excluded from the analyzes based on shifting trend assessed using the mean vector length (39).

The classification using tapping profile and the bad tappers is displayed via a bar graph fig. 42, the 3-tappers profile is the majority.



Figure 43: Distribution of tappers according to the entire sample (left) and according to the classes corresponding to the tempo (right).

The slower tempo (with a cycle made up of 225 ms elements) seems to contain less bad tappers.

However, given the small size of the sample, the statistical power is relatively low, i.e. the proportion of making a beta error (type 2, false positive) is high.

A chi-square test allows to see if there is a relationship of dependence between the tempo and the good or bad tapper classification.

The contingency table looks like this:

Tapper / Tempo	175 ms	200 ms	225 ms	all
Bad	7	7	4	18
Good	17	16	20	53
All	24	23	24	71

Table 3: Contingency table bad tappers across tempi.

Stat	P value	Degree of freedom
1.45	0.69	3

Table 4: Chi square sum up bad tappers across tempi.

The P-value does not suggest any relationship between the studied variables, the result is not statistically significant.

Distribution of tapping profiles after removal of bad tappers The distribution after filtering bad tappers can be viewed fig. 44.

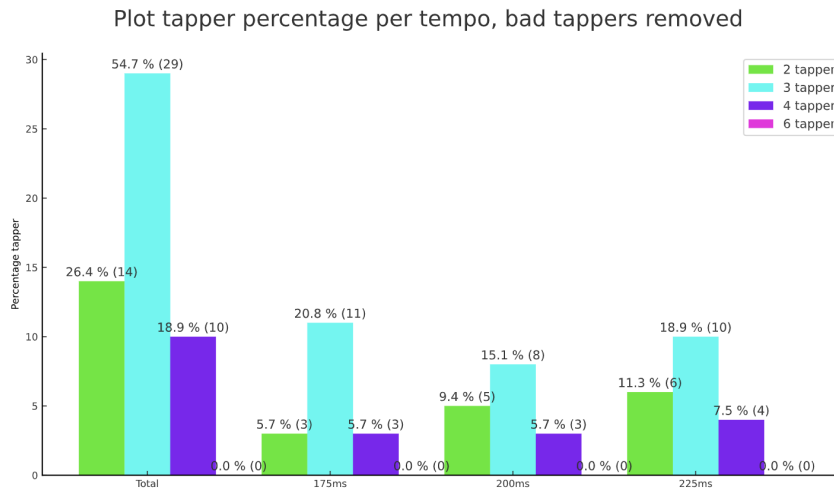


Figure 44: On the left: global distribution of taps . Second: distribution of taps in the fast tempo classe. Third: distribution of taps in the middle tempo classe. Right: distribution of taps in the slow tempo classe.

A chi square test on the contingency table, grouping the profiles of tapper after cleaning the bad tappers classified by tempi also shows no trend ($P = 0.848$, degree of freedom = 4) according to a statistic from Pearson's chi-squared. The predicted frequencies in the event of non-correlation between the variables (H_0) are close to the frequencies of the observations obtained even after removing the bad tappers.

Error per tap The distribution of good tappers between the different types of tapper is displayed fig. 45.

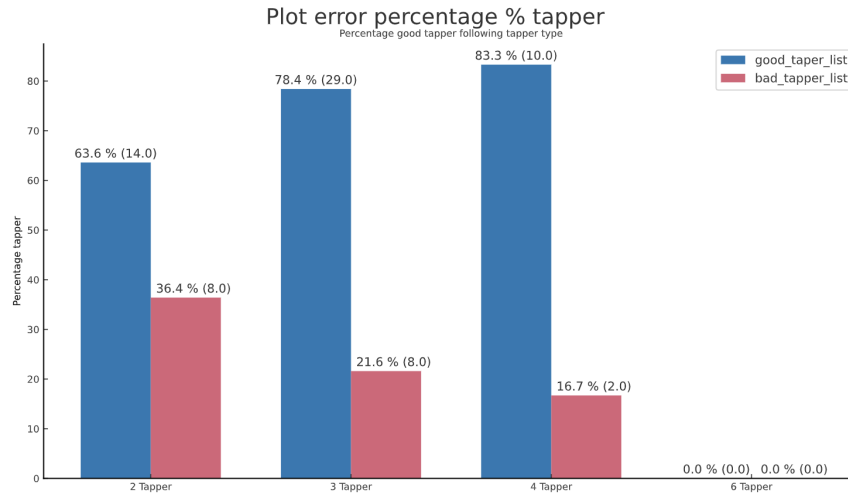


Figure 45: Distribution of the proportion of good tappers (blue) and bad tappers (red) between the different models of tapping behavior.

There is a higher proportion of bad tappers in the 2-tappers category. This trend is partly explained because the default model is the 2-tapper model, and "fits" the best with outlier tappers, this is a side effect of the argmin method between a tapping rate and theoretical ideal tapping rate used for the tapper profile classification (3.15.2).

4.2.5 categorization and performance

The methods based on Mean vector length are compared to a manual classification (3.15.3). The classification method seems efficient, however exceptional scenarios may arise that may noise the classification.

/	Detected as bad	Detected as good
Mean vector length method detected as bad	14	4
Mean vector length method Detected as good	2	51

Table 5: Contingency table bad tappers.

The classification accuracy is 92%. With a precision of 88%. We must be aware that the manual classification may be not perfect, these results should not be over interpreted and are in a qualitative level .

4.3 Time domain visualization

Analysis in the time domain is not done in this project (3.16), the frequency tagging method allows to perform efficiently analysis in the frequency domain.

However it is still interesting to have an overview of the EEG response in time domain, for viewing purpose.

The response elicited by the audio sequence throughout the trial by looking at the signal from the electrodes of the **region of interest (ROI)** can be visualized.

The overall response per sequence is calculated using epoch corresponding to a global mean of the EEG response when the audio sequence is presented. The result is an **evoked related potential (ERP)**.

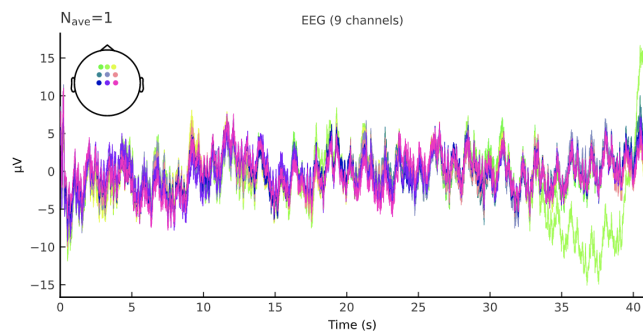


Figure 46: EEG response to a whole audio sequence, from a selection of the 9 frontocentral electrodes calculated by averaging long trial lasting epochs at fast tempo (175ms).

It is possible to cut the sequence according to the pattern cycle and next calculate the average response for a single pattern cycle period fig. 47.

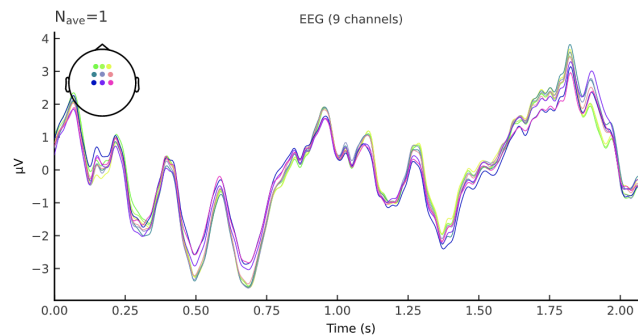


Figure 47: EEG response recorded on a selection of 9 frontocentral electrodes during a pattern cycle, calculated combining the sequence long response cut in sub epochs of the pattern cycle duration at fast tempo (175ms) and averaged.

The response is averaged among these 9 frontocentral electrodes making up the ROI.

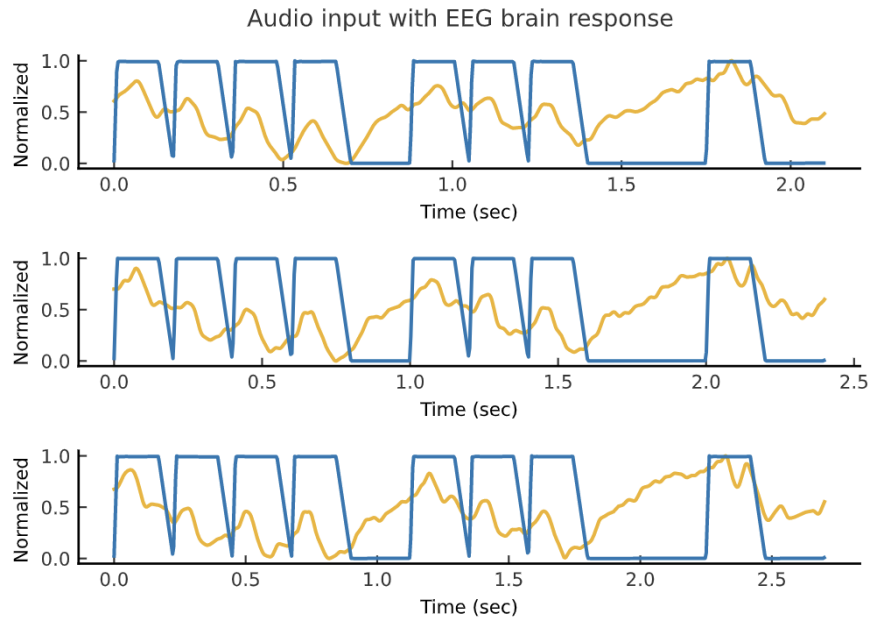


Figure 48: Evoked potential calculated on the average of the electrodes in the ROI for each pattern cycle. Top: fast tempo, Middle, medium tempo, bottom: slow tempo.

The response elicited according to a pattern cycle is targeted.

The EEG response reacts to the onset with a certain delay every time that an element of sound is presented during the pattern, peaks appear with a delay fig. 48 (position 1, 2, 3, 4, 6, 7, 8, 11).

During the periods of silences, the response seems increasing according to the duration of the silence.

4.4 Frequency analysis

4.4.1 Spectrum at frequencies of interest

It is possible to calculate and visualize this in the using SNR (3.17) to see if the signal analyzed is different (or not) from the signal outside of these interest frequencies considered as noise. Prominence of magnitudes at these frequencies is found.

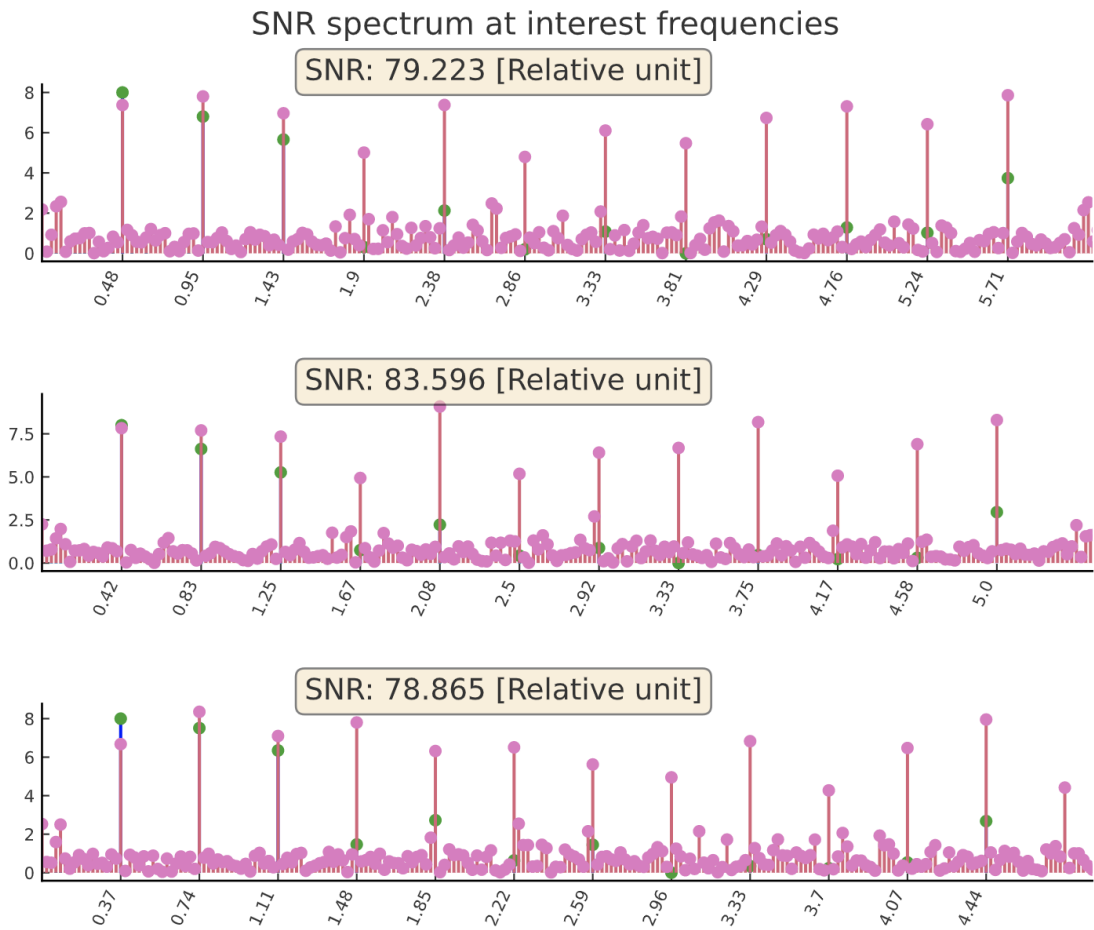


Figure 49: Visualization of the SNR, allowing to display and control the quality of the signal. Top: fast tempo, spectrum based SNR of the EEG response in response to sequence using pattern cycle composed of 175ms elements. Middle: medium tempo, spectrum based SNR of the EEG response in response to sequence using pattern cycle composed of 200ms elements. Bottom: slow tempo, spectrum based SNR of the EEG response in response to sequence using pattern cycle composed of 225ms elements. The score displayed is the sum of the SNR computed at frequencies of interest.

These SNR levels are acceptable, the frequencies of interest stand out well, the calculated score is based on the application of the kernel fig. 49, a ratio between sum at the frequency of interest and the average of the indirect neighbors.

The SNR is not changing significantly across tempi ($P > 0.05$).

Plot spectrum

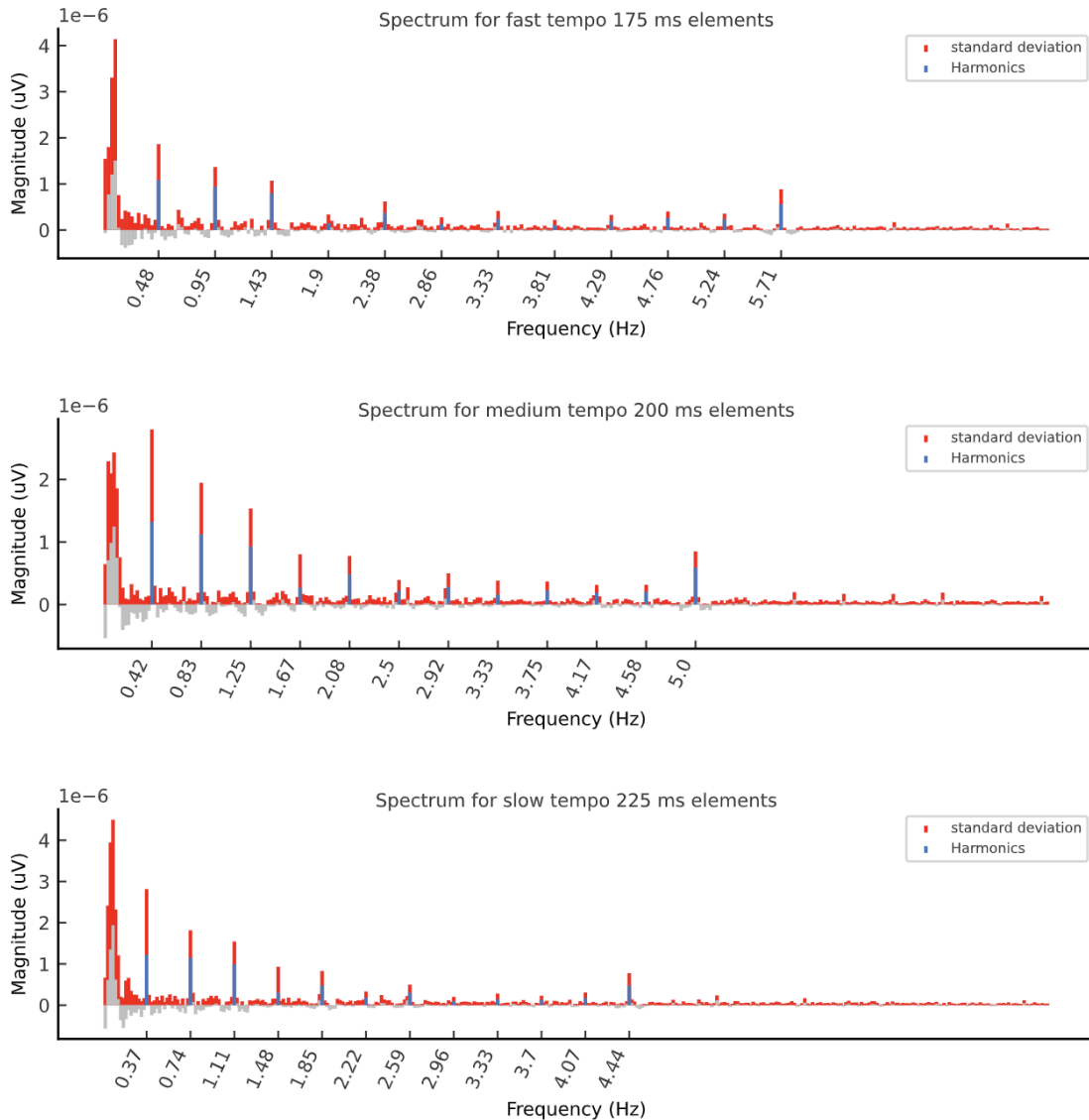


Figure 50: Representation of the average responses in the frequency domain of the EEG response to the presentation of the stimulus (Blue) frequencies of interest related to the input, (Red) representation of the standard deviation at each frequency.

Standard deviation visualization The fig. 50 represents the standard deviation (3.17) across the spectrum, at the frequencies of interest, the standard deviation is increased. This gain of std. is not totally due to the presence of noise which tend to be lower at phase lock processes after the preprocessing and averaging of the spectral response across the epochs. A further explanation is found by inspecting the individual responses of the participants, showing a high variability in the distribution of amplitudes at these frequencies of interest (low variability intra-participant, and high variability inter-participant).

4.4.2 Overall gain

The calculation of the general amplitude is done by summing the amplitudes at all the frequencies of interest in the spectrum (n=12) (3.17.1).

The mean general average sum of amplitudes is $5.56 * 10^{-6}$ uV (std. $3.02 * 10^{-6}$ uV).

The mean amplitude of the sum of the frequencies of interest at fast tempo is $5.05 * 10^{-6}$ uV (std. $1.38 * 10^{-6}$ uV).

The mean amplitude of the sum of the frequencies of interest at the average tempo is $5.99 * 10^{-6}$ uV (std. $3.52 * 10^{-6}$ uV).

The mean amplitude of the sum of the frequencies of interest at slow tempo is $5.63 * 10^{-6}$ uV (std. $3.56 * 10^{-6}$ uV).

The comparison between the summed amplitudes and the tempi is performed using an analysis of variance (ANOVA), and nothing suggests a statistical difference, so H1 is rejected, this is also verified via post hoc tests in the form of pairwise T- test fig. 51.

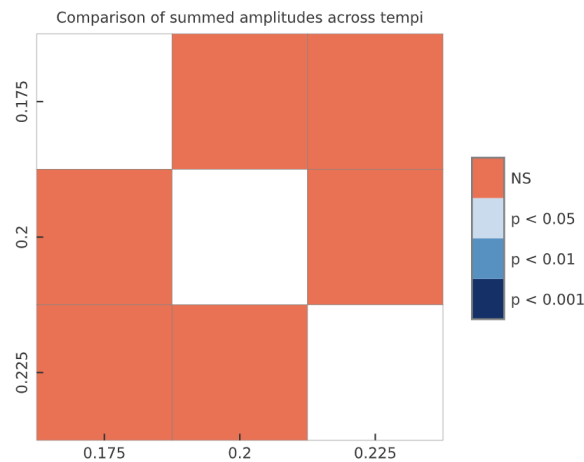
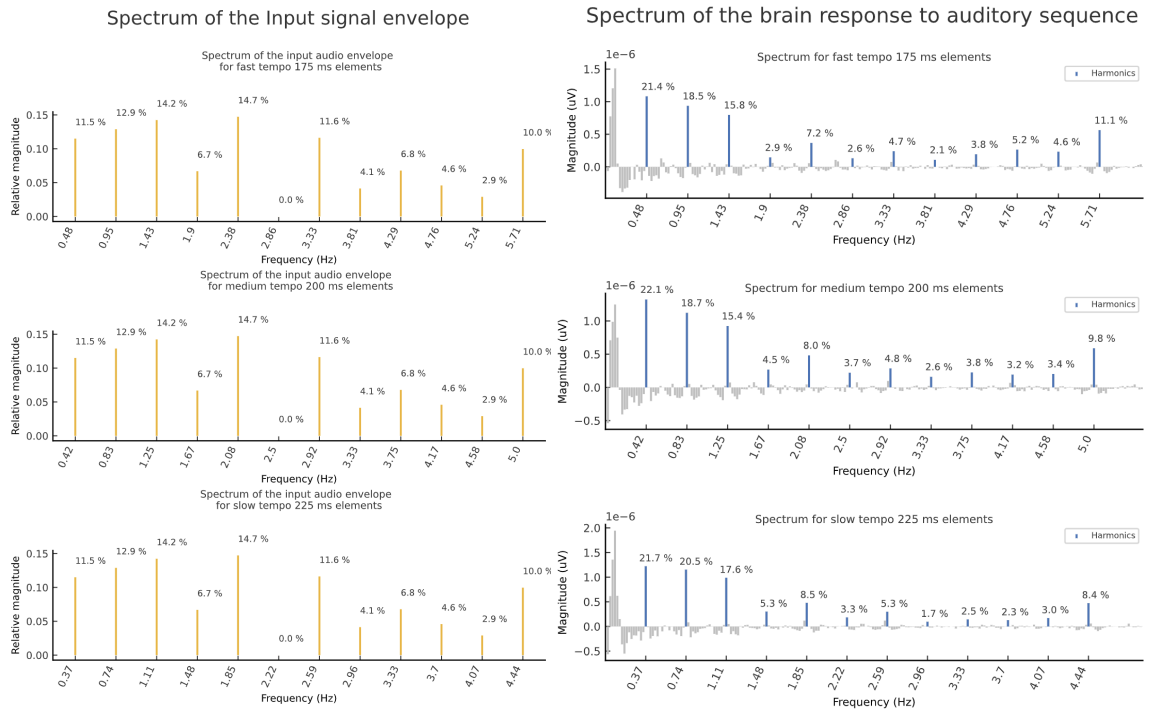


Figure 51: Results of pairwise T tests comparing summed amplitudes across tempi, no statistical difference have been found (orange means P value > 0.05).

4.4.3 Input - output comparison

This step compares the input-output, i.e. the comparison between the signal presented and the signal coming from the EEG (3.17.2).



(a) Representation of the spectrum of the envelope of the audio sequence represented to the participant during the listening trial. According to the 3 different tempi. Top: fast tempo, middle: medium tempo, bottom: slow tempo. The energy distribution is displayed at interest frequencies.

(b) Representation of the spectrum of the EEG response to the audio sequence. Top: fast tempo, middle: medium tempo, bottom: slow tempo. The energy distribution is displayed at interest frequencies.

Figure 52: Representation of the spectrum of the EEG response to the audio sequence. Top: fast tempo, middle: medium tempo, bottom: slow tempo. The energy distribution is also displayed.

The spectrum disposition of the audio stimulus presented corresponds to the spectrum disposition of the EEG response. On the other hand, the energy distribution displayed in fig. 52 through these different frequencies are indeed modified, output peaks are at the same places than input signal on the spectrum but magnitudes are not distributed in the same way.

A one-sample T-test tests the difference of frequencies (12) between input-output, this is repeated for each tempo (3). The results show significant differences ($P < 0.05$) even after Bonferonni-Holm correction. Except for the last frequency (11th harmonic) where P value is higher at each tempo.

The output spectrum show in this last interest frequency a more prominent peak, the energy seems concentrated here.

Except this last frequency, the spectrum between input and output are statistically different, H_0 can be rejected, the EEG response is not following the input signal without processing amplitudes.

4.4.4 Scalp distribution

It is possible to visualize the regions of interest where the amplitude of the frequencies are the most prominent and where the variation (standard deviation) is also prominent (3.17.3).

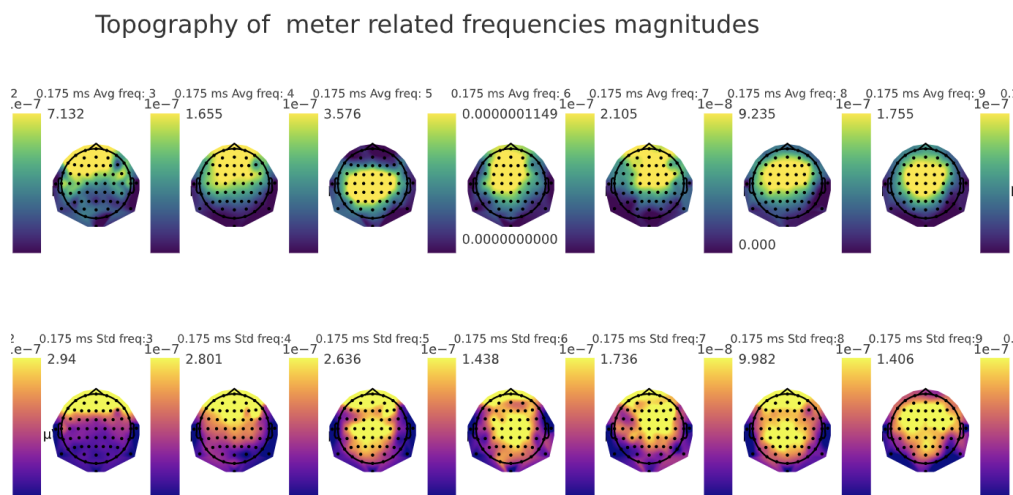


Figure 53: Topomap sample representing (above) cortical activity at each frequency of interest. Bottom: intensity of the standard deviation on the scalp for 7 frequencies of interest (all frequencies (12) and all tempi (3) are not represented for readability reasons).

fig. 53 displays the distribution of activity and standard deviation for the interest frequencies and according to the tempi, the activity is concentrated in the frontocentral regions.



Figure 54: Electrodes selected based on neurophysiology previous studies [4] and according to the intensity of the activity at the level of the sensor spatial domain determining the region of interest (ROI).

The subset of electrodes chosen is composed of the electrodes in these areas, capturing the highest activity during the listening trial. A subset corresponding to the ROI can therefore be selected fig. 54 containing the fronto-central electrodes.

4.4.5 Meter related frequencies

Based on tapping trial and the majority of 3 tappers, the assumption is made that the general tendency of the participants is to perceive 3 meters per pattern cycle, the frequencies used are therefore the 3 meters related frequencies fig. 55 (3.17.4).

3 meters related frequencies A 3-meters perceiver have frequencies of interest composed of the subset of harmonics composed of the 2nd harmonic, the 5th harmonic, the 8th harmonic and the 11th harmonic. The unrelated frequencies are composed of complementary harmonics to the quoted list.

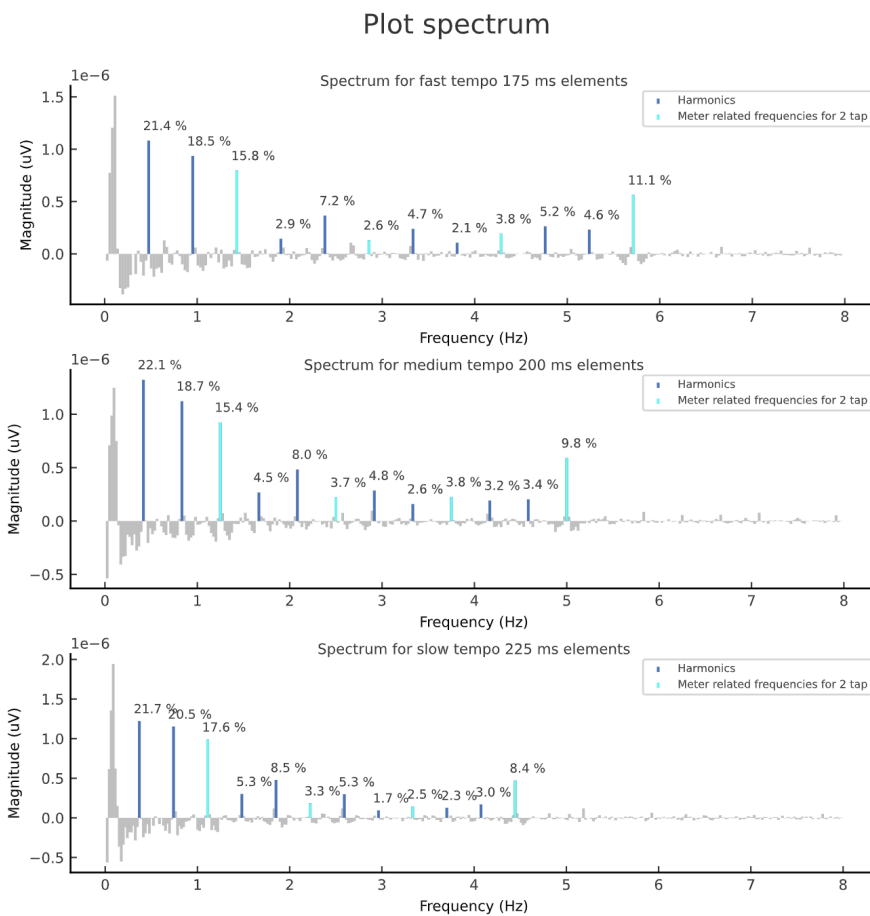


Figure 55: Representation of the 3 tapper meter related frequencies (Cyan) on interest frequencies corresponding to harmonics elicited by the input stimulus (Blue).

4.4.6 Z score meter related

For each participant the 3-meters related Z score is calculated using the average of Z score calculated at each 3-meters related frequencies (cyan peaks fig. 55, 3.17.4).

The mean 3-meters Z score is 0.094 (std. 0.299) overall, the mean 3-meters Z score is 0.068 (std. 0.275) for fast tempo (175ms), the mean 3-meters Z score is 0.118 (std. 0.332) for medium tempo (200ms), the mean 3-meters Z score is 0.096 (std. 0.285) for slow tempo (225ms).

Comparison input-output As the frequencies the z-score must be compared to the z score coming from the input sequence (3.17.4):

1. The z-score calculated from 3 meters related frequencies on the *input* audio sequence fig. 52 is equal to: -0.127 for each tempi.

The one sample T-test between input-output 3-meters Z scores are significantly different, for fast tempo (175ms), H0 is rejected (t-score = 2.35, $P < 0.039$), for medium tempo (200ms), H0 is rejected (t-score = 2.48, $P < 0.033$), for slow tempo (225ms), H0 is rejected (t-score = 2.59, $P < 0.025$). H0 is rejected at each tempo, the 3-meters Z score calculated on EEG response is different than the 3-meters Z score of the input at each tempo, Z scores are so significantly different between input and output for the 3-meters Z scores.

Comparison of 3-meters Z score across tempi This analysis compares the 3-meters Z scores of each participant between tempi (3.17.4).

Comparaison 3 meters related frequencies Z score across tempi.

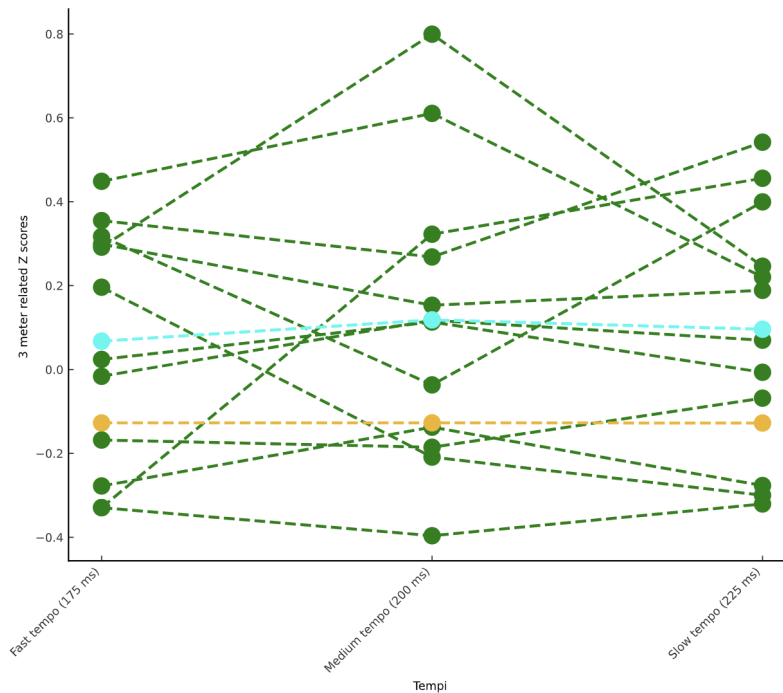


Figure 56: Representation of the 3-meter z scores between the times (dashed line green) and the average Z score between the participants (Cyan), the Z score of the input is also displayed (Yellow).

The fig. 56 represents the Z scores of each participant (Green) across tempi, the average Z score between the participants (Cyan) and the average Z scores of the input are also represented (Yellow).

To see if there is a statistical difference between the Z scores of the participants and between the tempi, an ANOVA is made, post hoc tests are also performed.

The ANOVA results ($F=0.27$, $P > 0.76$) show no differences between 3-meters Z scores across tempi, so H_1 is discarded, and H_0 is kept, suggesting that the 3-meters Z score does not vary between tempi.

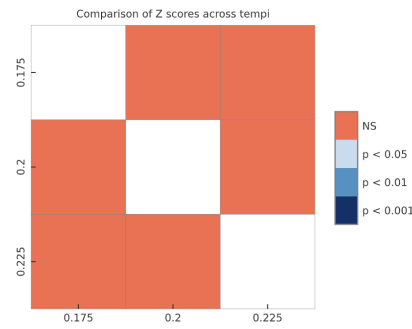


Figure 57: Representation of the post hoc tests as a pairwise T-test comparing the participants between the tempi, no values are above the alpha threshold (0.05), confirming the results of the ANOVA, showing no differences between the Z scores across tempi.

The post hoc tests do not reject this assumption fig. 57 and none expresses a P-value higher than alpha ($P > 0.05$), there are no differences between the Z scores across tempi

4.4.7 Summary

Many aspects have been explored in a general way there is no evidence of differences between the features explored and the tempi.

The SNR does not change between tempi, nor does the standard deviation.

A difference is found between the envelope of the presented input sequence and the signal from the EEG response.

The frequencies of interest seem attenuating when the tempo decreases at the higher harmonics, the energy is more concentrated on the lower harmonics fig. 52b.

Energy and energy variation appear to be localized around the frontocentral region electrodes, these electrodes are used to define the region of interest (ROI).

The z-scores are calculated between all these interest frequencies and a subset of harmonics, this subset composed of frequencies related to the frequency corresponding to an entire sub-period of the pattern cycle.

The subset chosen corresponds to 3-meters related frequencies because the tapping trial have shown a majority of 3-tapper (tapping behavior and meter perception are supposed to be correlated [13] [1]).

The 3-meters Z score are different between participants and the input audio sequence envelope.

However this Z score doesn't vary across the tempi between participants.

5 Discussion

How the beat and the meter is perceived in response to the same rhythmic pattern whose tempo changes slightly is an important question, for a finer understanding of cognitive and behavioral adaptations related to the meter perception. It is also important for understanding the general tendency how humans perceive these features of rhythm [60] (1.1.1) and which one influence the cognitive-motor action.

To answer to this question, a complex rhythm using previously studied pattern [15] is declined using 3 different tempi and were presented to participants.

This allows to validate previous experimental assumptions and observations and to use these known hypothesis for comparison.

Tapping across tempi The behavioral task shows different profiles of tappers, this plurality of tapping behavior could reflect the perception of the meter and the beat which, for the same rhythm varies between the participants as has already been observed [72]. A majority of tappers taps 3 times per cycle pattern, despite the plurality of responses, a general trend is observed of 3-tappers at our medium tempo (200ms) according to previous studies [15] and for slow (225ms) and fast (175ms) tempi.

The proportion of tappers profiles (2-3-4 tappers) does not vary between tempi, suggesting a certain invariance [73] and robustness [74] in the perception and production of the meter and beat when remaining in an human range for beat and meter perception [75] [11].

A lot of participants were successful in adapting to the change in tempo and maintaining a consistent tapping behavior suggesting some flexibility in the perceptual range of the beat when the tempo variation is slight [76].

The participants still perceive the meter and the beat every 3-4-6 events without massive reorganization of the meter perception as it can be the case when the tempo doubles or triples [10], where there is a reorganization of the meter perception by forming groups of number of elements significantly larger during a too pronounced acceleration of the tempo, for example a participant is originally tapping every 4 elements will tap every 12 elements during the acceleration of the tempo. This phenomenon is not encountered in the study carried out, even by looking the bad tappers, none behaviors are going in this direction. This suggest that a tempo limit has not been reached in our experiment.

The variation in **Tempo** of $\pm 13\%$ compared to the average tempo (200ms) always seems to be in the range of human meter perception [73], allowing an easy adaptation of the perception and the expression of the meter and the beat during slight variations of tempo [74].

Bad tappers across trials The analysis observed a high proportion of bad tappers, which were not synchronous with one of the subperiods of the pattern cycle period and therefore tapped in a biased way [32]. This can be explained by the difficulty of perceive the meter and the beat while listening to complex rhythms [15]. However, this avoids the induction of beat and meter perception as a metronome might do [15].

The ratio of bad tappers does not vary according to the tempo, the available data do not

show any difference between the proportion of good or bad tappers according to the tempo [11]. However, during the tapping task, some participants orally noticed more difficulties to perform the tapping task at the fast tempo (175ms). The tapping precision varies according to the tempo, and the precision drops (the std. increases) mainly during the fast tempo (4.2.1).

The slight change in tempo could therefore reduce the tapping precision and make the task perceptually more difficult for the participants, but does not particularly induce a bias and asynchrony in tapping.

However, these measurements and trends must be interpreted carefully, as the sample is relatively small and the high rate of bad tappers tends to diminish the already low statistical power, increasing our chances of doing type 2 errors (false negative), these assumptions could therefore be assessed by increasing the size of the sample in future version of this experiment. This comment is also valid for the proportion of tappers across the tempi [5].

However, some people have failed to synchronize to a pattern cycle subperiod and to detect a stable meter over time, this can be explained by other factors than the inability's to perceive beat and meter:

The results can be limited by biomechanical constraints [77], the participant physically can't tap according his perception of the beat and meter.

The failure of the task can be linked to other experimental factors, such as bad instructions from the experimenter, or a bad set up.

It may be due to a lack of attention [50], the maintenance of attention is required to understand in depth and succeed the synchronizing tapping task with complex sequences [15]. A general discomfort of the participant or a simple lack of attention due to fatigue can have a strong influence on the tapping results but also on the EEG results, whose poor results are harder to detect.

Input-output comparison The EEG response (output) can be compared to the response of the input Sequence (input), thanks to the frequency tagging [35], spectra are compared to the frequencies of interest. The position of the peaks on the spectrum of the EEG response corresponds to the position of the peaks on the spectrum of the sequence played.

However, the magnitudes at these frequencies of interest vary between input and output, suggesting that a nonlinear [78] transformation processed by structures related to the perception of the audio stimulus and the perception of rhythm and meter [23].

This nonlinear transformation is observed for each tempo, suggesting a similar processing of the input according to the tempo.

By using the general trend of 3-tappers during the tapping trial, the hypothesis is made that the perception of the meter is done according to 3-meters or cycle pattern periods .

According to previous studies [78] [23] a selective enhancement of frequencies related to this perception of the meter and the beat is carried out. We are therefore interested in the subset of frequencies relating to the 3-meter perception. These related frequencies are grouped together in the form of a Z score comparing the average of these related frequencies to the 3-meters perception and all the frequencies of interest.

The comparison between the 3-meters related Z score of the input and the output shows a

higher z score in the output [15].

Indicating that the frequency response for these 3-meters related frequencies is higher in the output. Neuronal populations could have therefore particularly enhanced these 3-meters related frequencies [23] [10] however no trend is observed between tempi.

Variation of Z scores The 3-meters related Z scores are calculated for each participant and for each **Tempo**. There is no evidence of variation in Z score across tempo. This suggests that the 3-meters related frequencies are enhanced as previously observed [15], there is a correlation between the behavior of 3 tapper and the selective enhancement of this 3-meters related frequencies. But this does not vary according to tempo, suggesting an invariance in the EEG response [11] and an adaptation of the perception of meter during slight changes in tempo.

However, even if the total energy of the response remains stable between tempi, the distribution of this energy changes according to tempo. When the **Tempo** decreases (slow tempo), the energy tends to concentrate at the lower frequencies of interest [11].

For example, for slower tempo **Sequence** EEG response, the elements constituting the pattern cycle presented are larger (225 ms), the last harmonic is less prominent, the EEG response is less pronounced to the event onset when the tempo slows down slightly.

Predominance of the last studied harmonic The frequency corresponding to the period of the former element of a pattern cycle (1/12), therefore aligned on the 11th harmonic (12th interest frequency) fig. 52 is prominent compared to the near previous frequencies resulting from the sub harmonics .

This prominence could be partially explained by low level processing of the auditory neurons responding to sound events [79] despite to a possible higher level processing linked to the meter and beat perception. However his energy tends to lower when tempo is slowing 5.

Spatial variation The activity seems to be stable on his spatial localization, the neuronal populations involved in meter perception could possibly be identical according to the previous experiments [67].

There is no clue of a spatial variation of the response across tempi, response seems prominent at the frontocentral level.

5.1 Conclusions

The project is still ongoing, the analysis of this sample leads to certain conclusions.

There are two major elements:

1. On one hand, the experiment agrees with a certain number of elements and hypotheses previously established and established during previous studies,
2. On the other hand, analysis are constantly limited by a lack of statistical power preventing us to analyze deeper.

This lack of statistical power is due to several factors, the first one is the creation of subdivisions with the addition of a new parameters in the study as a variation of tempo.

On the other hand, the parameters added as tempo variation are slight, unlike to previous studies [15] doubling or even tripling the base tempo (medium tempo), in the actual experiment the tempo variation is 15%, which obliges us to have finer observations or to increase the sample.

The small sample size also prevents us to analyze the minority behaviors.

This generalization is important to observe and to understand how behaviors are evolving according to the tempo, if the distribution of meter perception is varying across tempi and if it is linked with different meters related Z scores (2-4-6).

Indeed in this experiment we focus only on the 3-meters Z scores according to the general tapping trend, the used hypothesis 5 to perform analysis reflects the general meter perception trend but a finer classification could be done by looking Z scores for each tapping profiles (2-4-6 tapper), this classification is impossible to perform due to the limited size of our sample.

Increase the size of our sample could allow us to see smaller effect induced by variation of tempi and observe less common meter perception profile, higher the precision of data and analyses, higher the power and increasing analysis significance.

This could give information about robustness and persistence of the meter perception following slight changes of tempo.

Further analysis could use Bayesian statistic for example Bayes factor to assess Z-scores models, a subclassification using minority groups (2-4-6 tappers). Further steps in the development consider to use more advanced filters and automatic verification of EEG acquisition for the preprocessing step.

Next studies could continue to explore the meter and beat perception range by extending the variation of tempo.

6 Annex

6.1 Recruitment flyer



Expérience rémunérée : 30€ pour 2h00.

Bonjour,

Afin d'étudier la façon dont notre cerveau perçoit des rythmes musicaux, nous recherchons des participants pour une expérience à l'institut des neurosciences de l'UCL.

Le test consiste à enregistrer l'activité cérébrale via un système EEG en réponse à des stimuli sonores, et à mesurer les tapotements d'un doigt en fonction du rythme perçu. L'enregistrement par EEG (électroencéphalographie) est **indolore, non invasif** et nécessite simplement l'application d'un gel dans les cheveux pour améliorer la détection de l'activité cérébrale. Ce gel pourra être facilement nettoyé sur place à l'eau tiède.

Le test a lieu à l'institut des neurosciences (**Bâtiment 54 – Tour Claude Bernard - 54-55 Avenue Hippocrate, 1200 Bruxelles**), il dure en moyenne 2h30 et est rémunéré.

Pour participer il vous est demandé de répondre aux critères d'inclusion et de lire les informations relatives à l'expérience.

Les **contre-indications** pour participer à l'expérience sont les suivantes :

- Perte d'acuité auditive
- Avoir les cheveux tressés (incompatible avec l'EEG)
- Problème neurologique chronique ou psychiatrique connu
- Vous ou quelqu'un dans votre famille a des antécédents d'épilepsie

Si vous êtes intéressé.e.s et que vous ne présentez pas de critère.s d'exclusion (voir tableau ci-dessus), veuillez me contacter à l'adresse hadrien.cools@student.uclouvain.be en indiquant votre NOM, PRENOM, GSM, ainsi que vos disponibilités. N'hésitez pas non plus à me contacter au cas où vous auriez des questions.

Cools Hadrien

References

- [1] Tomas Lenc, Hugo Merchant, Peter E Keller, Henkjan Honing, Manuel Varlet, and Sylvie Nozaradan. Mapping between sound, brain and behaviour: four-level framework for understanding rhythm processing in humans and non-human primates. *Philos. Trans. R. Soc. Lond. B Biol. Sci.*, 376(1835):20200325, October 2021.
- [2] Laurel J Trainor, Xiaoqing Gao, Jing-Jiang Lei, Karen Lehtovaara, and Laurence R Harris. The primal role of the vestibular system in determining musical rhythm. *Cortex*, 45(1):35–43, January 2009.
- [3] Shannon Proksch, Daniel C Comstock, Butovens M  d  , Alexandria Pabst, and Ramesh Balasubramaniam. Motor and predictive processes in auditory beat and rhythm perception. *Front. Hum. Neurosci.*, 14, September 2020.
- [4] T. Lenc, H. Merchant, P. E. Keller, H. Honing, M. Varlet, and S. Nozaradan. Mapping between sound, brain and behaviour: four-level framework for understanding rhythm processing in humans and non-human primates. *Philos Trans R Soc Lond B Biol Sci*, 376(1835):20200325, 2021.
- [5] S. Nozaradan. Exploring how musical rhythm entrains brain activity with electroencephalogram frequency-tagging. *Philos Trans R Soc Lond B Biol Sci*, 369(1658):20130393, 2014.
- [6] S. Nozaradan, M. Sch  nwiesner, P. E. Keller, T. Lenc, and A. Lehmann. Neural bases of rhythmic entrainment in humans: critical transformation between cortical and lower-level representations of auditory rhythm. *Eur J Neurosci*, 47(4):321–332, 2018.
- [7] Michael Strotzer. One century of brain mapping using brodmann areas*. *Clinical Neuroradiology*, 19(3):179–186, 2009.
- [8] S. Nozaradan, A. Mouraux, J. Jonas, S. Colnat-Coulbois, B. Rossion, and L. Maillard. Intracerebral evidence of rhythm transform in the human auditory cortex. *Brain Struct Funct*, 222(5):2389–2404, 2017.
- [9] Steven J Luck. *An introduction to the event-related potential technique*. MIT press, 2014.
- [10] S. Nozaradan, I. Peretz, and A. Mouraux. Selective neuronal entrainment to the beat and meter embedded in a musical rhythm. *J Neurosci*, 32(49):17572–81, 2012.
- [11] Edward W. Large. *Resonating to musical rhythm : Theory and experiment*. 2008.
- [12] Jan Stupacher, Guilherme Wood, and Matthias Witte. Synchrony and sympathy: Social entrainment with music compared to a metronome. *Psychomusicology: Music, Mind, and Brain*, 27:158–166, 09 2017.
- [13] S. Nozaradan, P. E. Keller, B. Rossion, and A. Mouraux. Eeg frequency-tagging and input-output comparison in rhythm perception. *Brain Topogr*, 31(2):153–160, 2018.
- [14] Bruno H Repp. Sensorimotor synchronization: a review of the tapping literature. *Psychon. Bull. Rev.*, 12(6):969–992, December 2005.
- [15] S. Nozaradan, P. E. Keller, B. Rossion, and A. Mouraux. Eeg frequency-tagging and input-output comparison in rhythm perception. *Brain Topogr*, 31(2):153–160, 2018.
- [16] Fleur L Bouwer, J Ashley Burgoyne, Daan Odijk, Henkjan Honing, and Jessica A Grahn. What makes a rhythm complex? the influence of musical training and accent type on beat perception. *PLoS One*, 13(1):e0190322, January 2018.

- [17] Henkjan Honing, Fleur L Bouwer, and Gábor P Háden. Perceiving temporal regularity in music: the role of auditory event-related potentials (ERPs) in probing beat perception. *Adv. Exp. Med. Biol.*, 829:305–323, 2014.
- [18] Charles L Gary. The rhythmic structure of music. *J. Res. Music Educ.*, 9(1):77–78, April 1961.
- [19] Bastiaan van der Weij, Marcus T Pearce, and Henkjan Honing. A probabilistic model of meter perception: Simulating enculturation. *Front. Psychol.*, 8:824, May 2017.
- [20] Sylvie Nozaradan, Peter E Keller, Bruno Rossion, and André Mouraux. EEG frequency-tagging and input-output comparison in rhythm perception. *Brain Topogr.*, 31(2):153–160, March 2018.
- [21] Jessica A Grahn and Matthew Brett. Rhythm and beat perception in motor areas of the brain. *J. Cogn. Neurosci.*, 19(5):893–906, May 2007.
- [22] Jessica A Grahn. The role of the basal ganglia in beat perception: neuroimaging and neuropsychological investigations. *Ann. N. Y. Acad. Sci.*, 1169(1):35–45, July 2009.
- [23] Karl D. Lerud, Felix V. Almonte, Ji Chul Kim, and Edward W. Large. Mode-locking neurodynamics predict human auditory brainstem responses to musical intervals. *Hearing Research*, 308:41–49, 2014. Music: A window into the hearing brain.
- [24] Frederik Styns, Leon van Noorden, Dirk Moelants, and Marc Leman. Walking on music. *Hum. Mov. Sci.*, 26(5):769–785, October 2007.
- [25] Bruno H Repp and Yi-Huang Su. Sensorimotor synchronization: a review of recent research (2006-2012). *Psychon. Bull. Rev.*, 20(3):403–452, June 2013.
- [26] C Drake, M R Jones, and C Baruch. The development of rhythmic attending in auditory sequences: attunement, referent period, focal attending. *Cognition*, 77(3):251–288, December 2000.
- [27] EDWARD W. LARGE and JOHN F. KOLEN. Resonance and the perception of musical meter. *Connection Science*, 6(2-3):177–208, 1994.
- [28] Jessica M Ross, John R Iversen, and Ramesh Balasubramaniam. The role of posterior parietal cortex in beat-based timing perception: A continuous theta burst stimulation study. *J. Cogn. Neurosci.*, 30(5):634–643, May 2018.
- [29] Jessica A Grahn and Matthew Brett. Rhythm and beat perception in motor areas of the brain. *J. Cogn. Neurosci.*, 19(5):893–906, May 2007.
- [30] Daniel O Claassen, Catherine R G Jones, Minhong Yu, Georg Dirnberger, Tim Malone, Michael Parkinson, Paola Giunti, Michael Kubovy, and Marjan Jahanshahi. Deciphering the impact of cerebellar and basal ganglia dysfunction in accuracy and variability of motor timing. *Neuropsychologia*, 51(2):267–274, January 2013.
- [31] Matthias Guggenmos, Philipp Sterzer, and Radoslaw Martin Cichy. Multivariate pattern analysis for MEG: A comparison of dissimilarity measures. *Neuroimage*, 173:434–447, June 2018.
- [32] Almudena Capilla, Paula Pazo-Alvarez, Alvaro Darriba, Pablo Campo, and Joachim Gross. Steady-state visual evoked potentials can be explained by temporal superposition of transient event-related responses. *PLoS One*, 6(1):e14543, January 2011.
- [33] R Näätänen. Implications of ERP data for psychological theories of attention. *Biol. Psychol.*, 26(1-3):117–163, June 1988.

- [34] Almudena Capilla, Paula Pazo-Alvarez, Alvaro Darriba, Pablo Campo, and Joachim Gross. Steady-state visual evoked potentials can be explained by temporal superposition of transient event-related responses. *PLoS One*, 6(1):e14543, January 2011.
- [35] Anthony M. Norcia, L. Gregory Appelbaum, Justin M. Ales, Benoit R. Cottureau, and Bruno Rossion. The steady-state visual evoked potential in vision research: A review. *Journal of Vision*, 15(6):4–4, 05 2015.
- [36] Erika Skoe and Nina Kraus. Auditory brain stem response to complex sounds: a tutorial. *Ear Hear.*, 31(3):302–324, June 2010.
- [37] Steven J Luck. *An introduction to the event-related potential technique*. MIT press, 2014.
- [38] Steven J Luck, Andrew X Stewart, Aaron Matthew Simmons, and Mijke Rhemtulla. Standardized measurement error: A universal metric of data quality for averaged event-related potentials. *Psychophysiology*, 58(6), June 2021.
- [39] Terence W Picton, M Sasha John, Andrew Dimitrijevic, and David Purcell. Human auditory steady-state responses. *Int. J. Audiol.*, 42(4):177–219, June 2003.
- [40] M Tsuzaki. Recent trends in the psychology of music perception: the perceptual processes of melody and musical pitch. *Shinrigaku Kenkyu*, 59(3):176–190, August 1988.
- [41] M Ezawa. Rhythm perception equipment for skin vibratory stimulation. *IEEE Eng. Med. Biol. Mag.*, 7(3):30–34, 1988.
- [42] Lingxi Lu, Jingwei Sheng, Zhaowei Liu, and Jia-Hong Gao. Neural representations of imagined speech revealed by frequency-tagged magnetoencephalography responses. *Neuroimage*, 229(117724):117724, April 2021.
- [43] J Ph Lachaux, D Rudrauf, and P Kahane. Intracranial EEG and human brain mapping. *J. Physiol. Paris*, 97(4-6):613–628, July 2003.
- [44] Dries De Kegel. Tissue-level tolerance criteria for crash-related head injuries: A combined experimental and numerical approach, 2018.
- [45] D Lehmann. EEG assessment of brain activity: Spatial aspects, segmentation and imaging. *Int. J. Psychophysiol.*, 1(3):267–276, March 1984.
- [46] Matthias Guggenmos, Philipp Sterzer, and Radoslaw Martin Cichy. Multivariate pattern analysis for MEG: A comparison of dissimilarity measures. *Neuroimage*, 173:434–447, June 2018.
- [47] Manon Grube and Timothy D Griffiths. Metricity-enhanced temporal encoding and the subjective perception of rhythmic sequences. *Cortex*, 45(1):72–79, January 2009.
- [48] W Lang, H Obrig, G Lindinger, D Cheyne, and L Deecke. Supplementary motor area activation while tapping bimanually different rhythms in musicians. *Exp. Brain Res.*, 79(3):504–514, 1990.
- [49] Md Kafiul Islam, Amir Rastegarnia, and Zhi Yang. Methods for artifact detection and removal from scalp EEG: A review. *Neurophysiol. Clin.*, 46(4-5):287–305, November 2016.
- [50] Fleur Bouwer, Carola Werner, Myrthe Knetemann, and Henkjan Honing. Disentangling beat perception from sequential learning and examining the influence of attention and musical abilities on erp responses to rhythm. *Neuropsychologia*, 85, 03 2016.

- [51] Fleur L Bouwer and Henkjan Honing. Temporal attending and prediction influence the perception of metrical rhythm: evidence from reaction times and ERPs. *Front. Psychol.*, 6:1094, July 2015.
- [52] Eleanor M. Dunn and Madeleine M. Lowery. Simulation of pid control schemes for closed-loop deep brain stimulation. In *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*, pages 1182–1185, 2013.
- [53] Tomas Lenc, Peter E. Keller, Manuel Varlet, and Sylvie Nozaradan. Reply to rajendran and schnupp: Frequency tagging is sensitive to the temporal structure of signals. *Proceedings of the National Academy of Sciences*, 116(8):2781–2782, 2019.
- [54] Tzu-Han Zoe Cheng, Sarah C Creel, and John R Iversen. How do you feel the rhythm: Dynamic motor-auditory interactions are involved in the imagination of hierarchical timing. *J. Neurosci.*, 42(3):500–512, January 2022.
- [55] Kate E Williams. Moving to the beat: Using music, rhythm, and movement to enhance self-regulation in early childhood classrooms. *Int. J. Early Child.*, 50(1):85–100, April 2018.
- [56] Marijn van Vliet. Seven quick tips for analysis scripts in neuroimaging. *PLOS Computational Biology*, 16(3):1–10, 03 2020.
- [57] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A. Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, Lauri Parkkonen, and Matti S. Hämäläinen. MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(267):1–13, 2013.
- [58] Alain de Cheveigné. Zapline: a simple and effective method to remove power line artifacts. *bioRxiv*, 2019.
- [59] Jurgen Dammers, Michael Schiek, Frank Boers, Carmen Silex, Mikhail Zvyagintsev, Uwe Pietrzyk, and Klaus Mathiak. Integration of amplitude and phase statistics for complete artifact removal in independent components of neuromagnetic recordings. *IEEE Transactions on Biomedical Engineering*, 55(10):2353–2362, 2008.
- [60] Jaakko Malmivuo and Robert Plonsey. *Bioelectromagnetism. 28. The Electric Signals Originating in the Eye*, pages 437–447. 01 1995.
- [61] Alain de Cheveigné and Dorothée Arzounian. Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data. *Neuroimage*, 172:903–912, May 2018.
- [62] Alain de Cheveigné, Giovanni M Di Liberto, Dorothée Arzounian, Daniel D E Wong, Jens Hjortkjær, Søren Fuglsang, and Lucas C Parra. Multiway canonical correlation analysis of brain data. *Neuroimage*, 186:728–740, February 2019.
- [63] Alain de Cheveigné and Lucas C Parra. Joint decorrelation, a versatile tool for multichannel data analysis. *Neuroimage*, 98:487–505, September 2014.
- [64] Alain de Cheveigné. Sparse time artifact removal. *J. Neurosci. Methods*, 262:14–20, March 2016.
- [65] Pauline Tranchant, Dominique T. Vuvan, and Isabelle Peretz. Keeping the beat: A large sample study of bouncing and clapping to music. *PLOS ONE*, 11(7):1–19, 07 2016.
- [66] Noémie Hébert-Lalonde, Lionel Carmant, Dima Safi, Marie-Sylvie Roy, Maryse Lassonde, and Dave Saint-Amour. A frequency-tagging electrophysiological method to identify central and peripheral visual field deficits. *Documenta ophthalmologica. Advances in ophthalmology*, 129, 05 2014.

- [67] Sylvie Nozaradan, Peter E Keller, Bruno Rossion, and André Mouraux. EEG frequency-tagging and input-output comparison in rhythm perception. *Brain Topogr.*, 31(2):153–160, March 2018.
- [68] Yi-Huang Su and Ernst Pöppel. Body movement enhances the extraction of temporal structures in auditory sequences. *Psychol. Res.*, 76(3):373–382, May 2012.
- [69] PETRI TOIVIAINEN and JOEL S. SNYDER. Tapping to Bach: Resonance-Based Modeling of Pulse. *Music Perception*, 21(1):43–80, 09 2003.
- [70] Hugo Merchant, Deborah L Harrington, and Warren H Meck. Neural basis of the perception and estimation of time. *Annu. Rev. Neurosci.*, 36:313–336, July 2013.
- [71] Ralph B D’Agostino. An omnibus test of normality for moderate and large size samples. *Biometrika*, 58(2):341, August 1971.
- [72] G M Edelman and J A Gally. Degeneracy and complexity in biological systems. *Proc. Natl. Acad. Sci. U. S. A.*, 98(24):13763–13768, November 2001.
- [73] Stewart H. Hulse, Annie H. Takeuchi, and Richard F. Braaten. Perceptual Invariances in the Comparative Psychology of Music. *Music Perception*, 10(2):151–184, 12 1992.
- [74] Edward W Large and Mari Riess Jones. The dynamics of attending: How people track time-varying events. *Psychological review*, 106(1):119, 1999.
- [75] Bruno Repp. Rate limits of sensorimotor synchronization. *Advances in Cognitive Psychology*, 2, 01 2006.
- [76] Daniel Bendor and Xiaoqin Wang. Differential neural coding of acoustic flutter within primate auditory cortex. *Nat. Neurosci.*, 10(6):763–771, June 2007.
- [77] Fred Cummins. Rhythm as an affordance for the entrainment of movement. *Phonetica*, 66:15–28, 02 2009.
- [78] Molly J. Henry, Björn Herrmann, and Jessica A. Grahn. What can we learn about beat perception by comparing brain signals and stimulus envelopes? *PLOS ONE*, 12(2):1–17, 02 2017.
- [79] A M Aertsen and P I Johannesma. The spectro-temporal receptive field. a functional characteristic of auditory neurons. *Biol. Cybern.*, 42(2):133–143, 1981.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
École polytechnique de Louvain

Rue Archimède, 1 bte L6.11.01, 1348 Louvain-la-Neuve, Belgique | www.uclouvain.be/epl