Project for Signal Processing Course

MICRODANCE :

Analysis of Unconscious Micromotion during Listening to different Sound Stimulus

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1 Introduction

With the development of streaming services and super fast and small gadgets, music became an irreplaceable part of everyday life for millions. As listeners we know, that different music influence the way we feel: listening to some lively “beat” can make us feel more cheerful and energetic, or otherwise sometimes in the sad mood we are likely to listen to some heavy, slow, in minor gamma music, which can plunge us deeper into ourselves and our thoughts.

Also, we used to listen to different genres due to the kind of activity. I can’t imagine hearing some classical music (like Mozart) in the gym or some drum and bass music during the yoga class. From this thought, we can consider that different features in music definitely influence the way we feel and even move. Some music can help us concentrate but some make us feel ready to dance all night.

So the question raised in this introductory work into ‘micromotion vs music’ is to look overall at statistics and find correlations between how people can ‘stand still’ while listening to different music, which parameters (as musical experience or age of human) and features of music influence human on the unconscious micromovement level.

2.1 Experiment description and data

The experiment was set in 2015 in Oslo. Different people were asked to stand as still as possible while listening 360 secs of 4 different stimuli in a different order (music: EDM, Salsa, Meditation, Silence). Micromovement of their heads was captured by 9 cameras of Qualisys motion capture system.

Each participant filled the questionnaire with such information:

Questions:
1. Age 2. Gender 3. How many hours do you spend on average per week listening to music 4. How many hours do you spend on average per week to play/produce/compose music 5. How many hours do you spend on average per week dancing (both as training and at a party) 6. How many hours do you spend on average per week to train (other than dance) 7. Do you think it was tiring (experiment)? 8. How much did you feel moving (compared to standing still)? 9. Did you find that you moved more while listening to music? 10. Did you keep your eyes open? 11. Did you lock your knees?

The data was presented in 3 dimensions:

1. Movement data - 12 files with experiments with 3-12 people in each: X, Y, Z coordinates in real-time for the participant during 360 seconds of listening to 6 parts of the music in a special order for each experiment. 36000 rows per axes, sample frequency = 100Hz.

   X - moving sideways
   Y - moving front and back
   Z - moving up-down

2. Stimuli (sounds) - .wav files for 60 seconds of each stimuli music type: EDM, Salsa, Meditation, and Silence.
3. Questionnaire answers.

2.2 Data Processing Strategy

My approach in this work will be **exploratory** and **descriptive.** As a goal, I set myself to find some relations and explore (once more) what interesting characteristics we can get from such data combination.

I would try to move through datasets and figure out how to get useful features from them. Also, I will base on already investigated approaches in these fields of signal processing.

General technics which will be used in this research:

- Displacement
- FFT and SFTF
- Filters applying
- Data aggregation (statistics)

3.1 Signal Processing - Time Series Movement Patterns

Starting with movements data. Here is an example of how signal for a special participant standing still for 360 seconds looks like:

Figure 1. Raw Signal for X, Y, Z axes

This data represents the movement of participant head-point during the experiment. So axis for volume shows data in relation to all space around. I was interested in the displacement feature to know the exact value of movement between each time point.

displacement (data) = *|| data[n] - data[n - 1] ||*

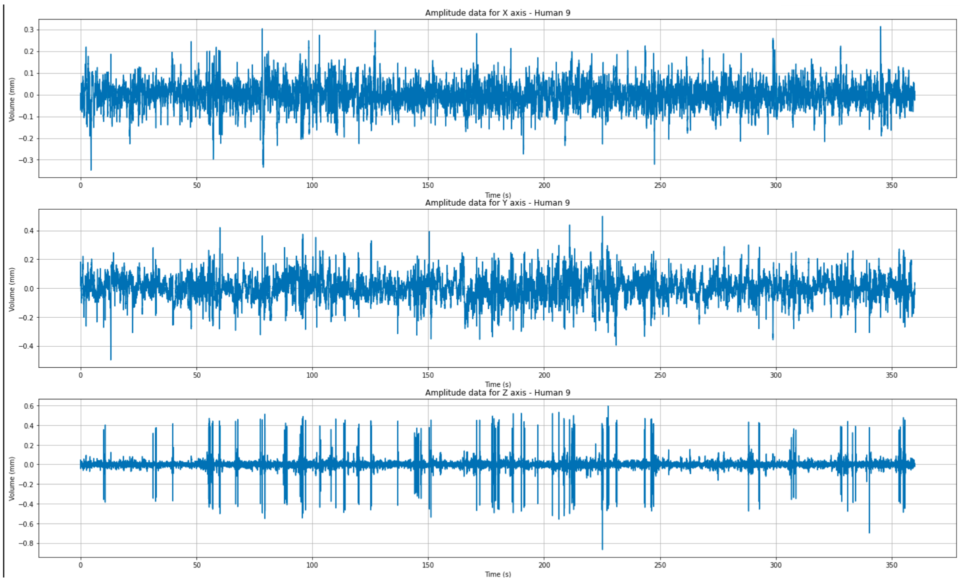

Figure 2. Displacement Signal for X, Y, Z axes

In Figure 2. we can see a signal for 360 seconds. Let's divide it into parts corresponding to the order of stimuli.

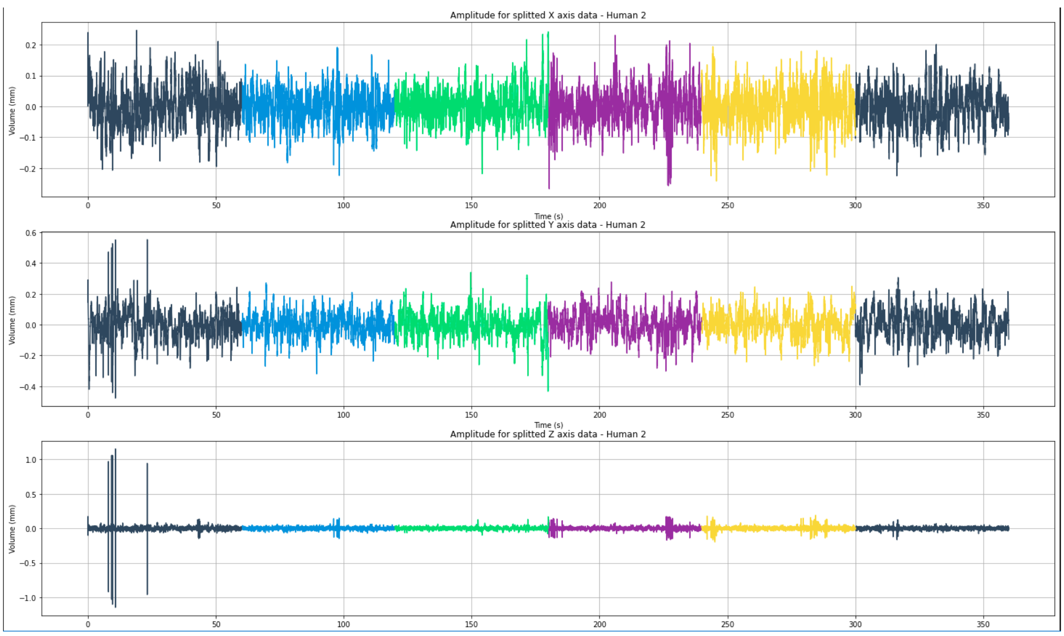

Figure 3. Displacement Signal for X, Y, Z axes divided due to stimuli types

Now it would be nice to look closer at the special part signal. Example of plot and its amplitude spectrum:

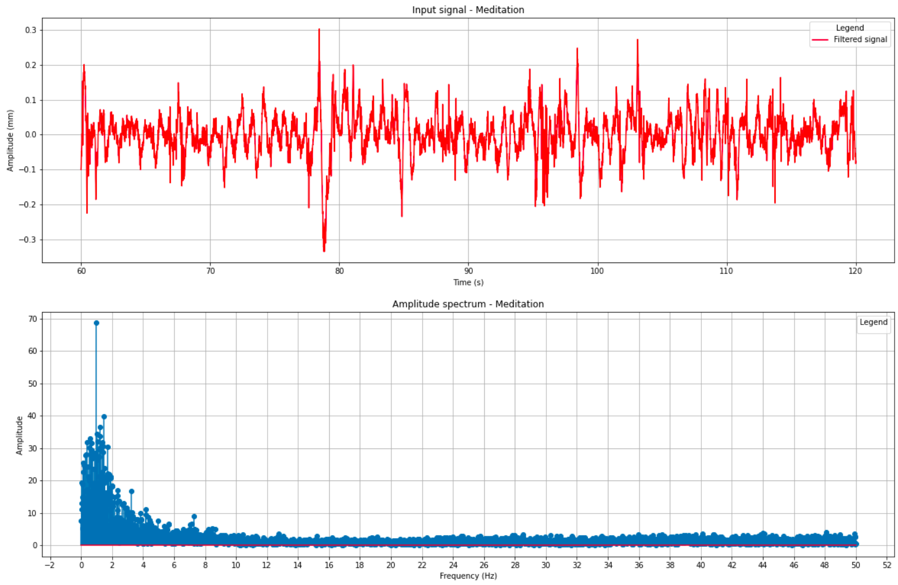

Figure 4.1. Part = Meditation, Signal and Spectrogram for X-axis movement

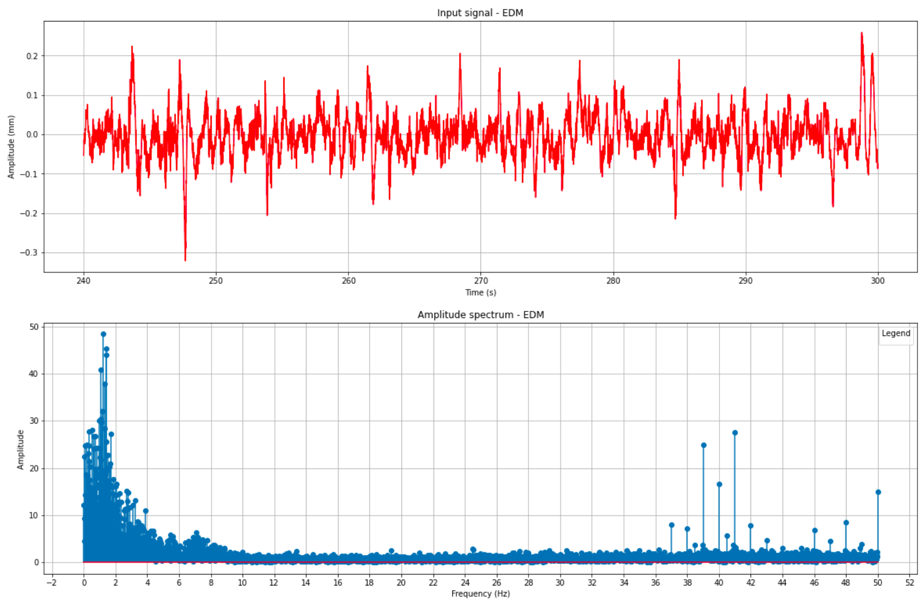

Figure 4.2 Part = EDM, Signal and Spectrogram for X-axis movement

While observing such data through all stimuli types, I noticed that all of the signals have quite the same pattern around 0 - 10 Hz, average at 25 amplitude value and Maximum between 40-70 values. But only for **EDM,** there were significantly different values of 35 - 50Hz.

To explore more those frequencies, I will use a high-pass Butterworth filter and apply it to our signal. It should fit our conditions because all we need is just smooth removal of all 'not interesting' for now frequences.

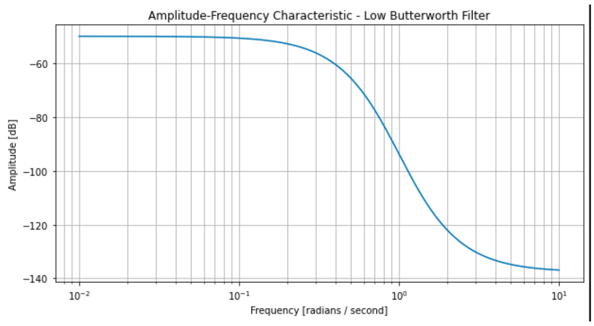

Figure 5. High-pass Butterworth filter Amplitude-Frequency Characteristic

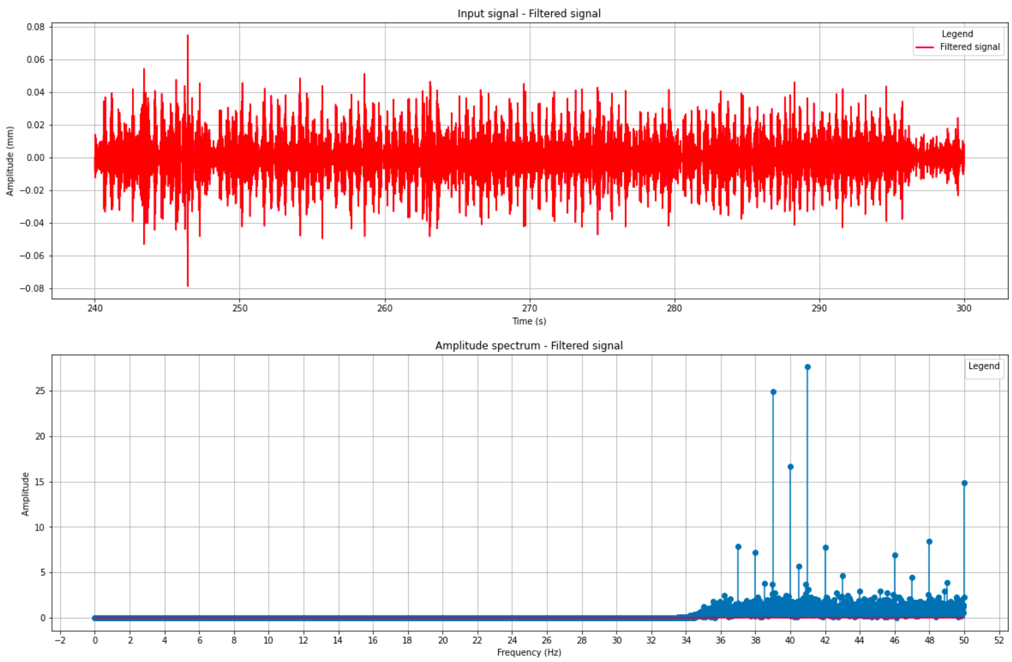

Figure 6. Part = EDM, Signal and Spectrogram for X-axis movement after applying filter

Now we can notice some patterns in the signal. Lets remember it for now and get back to this result while processing the sound information.

3.2 Signal Processing - Statistics

We need some value to compare different classes to each other. To find an average **Speed of Motion** (SoM) for some samples I will add all displacement points together and divide them by time duration. **SoM** will be represented as *mm/s.* This value will give us a better understanding of the average dynamic per class.

$$\textbf{SoM} = \textbf{displacement}(data) / time$$

Now we can measure the micro-movement power. Firstly I would like to make a test for listening to *Music* or *Silence*. The mean **SoM** of aggregated values for all participants will be:

	X_mean	*X_std*	*Y_mean*	*Y_std*	*Z_mean*	*Z_std*
Music	3.66	0.552	5.37	0.666	1.5	0.402
Silence	3.792	0.612	5.622	0.672	1.512	0.432

*Figure 7. Statistics of **SoM** of each axis for listening to Music or Silence in the experiment (mm/s)*

From the above table, we can conclude that mean **SoM** Mean and STD for most of the *Silence* axes are bigger than while listening to *Music.* So people move more actively while listening to nothing.

Let's go further and find those values for **different Stimuli types**. But this time we will separate observing signals by participants specifics. From the questionnaire data, it's possible to separate humans into 2 groups: people who spend time with music (listen or create) more than 25 hours per week and those who are less.

For all observations of people for listening music:
*Min = **0** hours/week Mean = **18** hours/week Max = **70** hours/week*

For all observations of people who create music:
*Min = **0** hours/week Mean = **4.9** hours/week Max = **30** hours/week*

In future texts, they will be called ***Musicians*** and ***Not musicians.*** This separation will give some life background of people to help us find correlation due to participant experience.

Musicians	*X_SoM*	*Y_SoM*	*Z_SoM*
Starting Silence	4.05	5.98	1.61
Meditation	4.13	5.78	1.46
Salsa	4.03	5.76	1.43
EDM	4.16	5.51	1.60
Silence Ending	4.66	6.48	1.52

Figure 8.1 ***Musicians*** *SoM statistics for each axis and stimuli type*

Not Musicians	*X_SoM*	*Y_SoM*	*Z_SoM*
Starting Silence	3.10	4.92	1.43
Meditation	3.22	5.07	1.45
Salsa	3.18	4.97	1.41
EDM	3.22	5.10	1.61
Silence Ending	3.33	5.08	1.48

Figure 8.2 ***Not Musicians*** *SoM statistics for each axis and stimuli type*

Those tables give us a lot of information and some important outcomes from all this experiment. By now we can absolutely say that **stimuli type influences the way of our unconscious moves**. Let's dive deeper into this observation.

Comparing Different Stimuli

To start with, it's important to say that **Y-axis shows the highest SoM** value. It means that people during standing and listening stimuli were moving back and front the most. The X-axis was average and Z-axis shows the least **SoM**.

The highest value of the Z-axis was for the EDM Stimuli type (but it was also quite high for Musicians at Starting Silence).
For both classes, the most ‘movable’ part on X and Y axes was the **Silence Ending** - 60 seconds ‘standing still’ in silence after all kinds of music. My assumption is that it is caused by:

1) *Surprising fact* - that music ended, also the fact that experiment will be finished soon can also excite.
2) *Absent music pattern* - it could ‘structure’ some waves of micromovement and when it has gone - some unconscious rhythmics inside the brain just broken up.

EDM stimuli type shows the biggest SoM of all Music stimuli for **Not Musicians.** (but **Meditation** is not far away). Also, **EDM** shows leads in the top for Z-axis for both classes.

For **Musicians**, **EDM** is also quite high but really close to the **Meditation** which gives the highest SoM for the Y-axis of all the music stimuli (Meditation: 5.78 mm/s).

The main difference between **EDM** and **Salsa** for 2 classes was that **Musicians** are significantly more active at Y-axis in **Salsa** (Salsa: 5.76 mm/s, EDM: 5.51 mm/s) when for **Not Musicians** Y-axis SoM value was a bit more for **EDM** (EDM: 5.10 mm/s, Salsa: 4.97 mm/s)

Comparing Classes

At this point, we have proof that the **Musicians** class reacts more than **Not Musicians** to different stimuli types (by the average value of all statistics). It means that people who interact more with music in real life are becoming more sensitive to sounds and it can be seen even through the unconscious micro-moves made while people were asked to stand as still as possible. This fact says about experience value and that it really matters.

Let’s take 2 new classes for participants age: **Under 25 y.o.** and **After 25 y.o.**

Under 25 y.o.	*X_SoM*	*Y_SoM*	*Z_SoM*
Starting Silence	3.70	5.40	1.64
Meditation	3.88	5.40	1.58
Salsa	3.77	5.29	1.54
EDM	3.88	5.13	1.68
Silence Ending	4.25	5.90	1.62

Figure 8.3 ***Under 25*** *SoM statistics for each axis and stimuli type*

After 26 y.o.	*X_SoM*	*Y_SoM*	*Z_SoM*
Starting Silence	3.07	5.67	1.01
Meditation	2.86	5.50	0.97
Salsa	2.95	5.68	0.93
EDM	2.94	6.01	1.30
Silence Ending	2.97	5.31	1.00

Figure 8.4 ***After 26*** *SoM statistics for each axis and stimuli type*

The first thing which is quite different from previous classes is that **After 26** participants it was ‘easier’ to stand still at the end of the experiment in **Silence Ending** than at the start.

Also **After 26** shows significantly fewer SoM values on X and Z axes than **Under 25.** But at the same time has higher values at Y-axis.

For **Under 25** most movable genres of stimuli were Meditation and EDM while for **After 26** were EDM and Salsa.

3.3 Signal Processing - Sound data vs Movement data

During movement data processing we applied a filter on the EDM movements signal part and had the next plots:

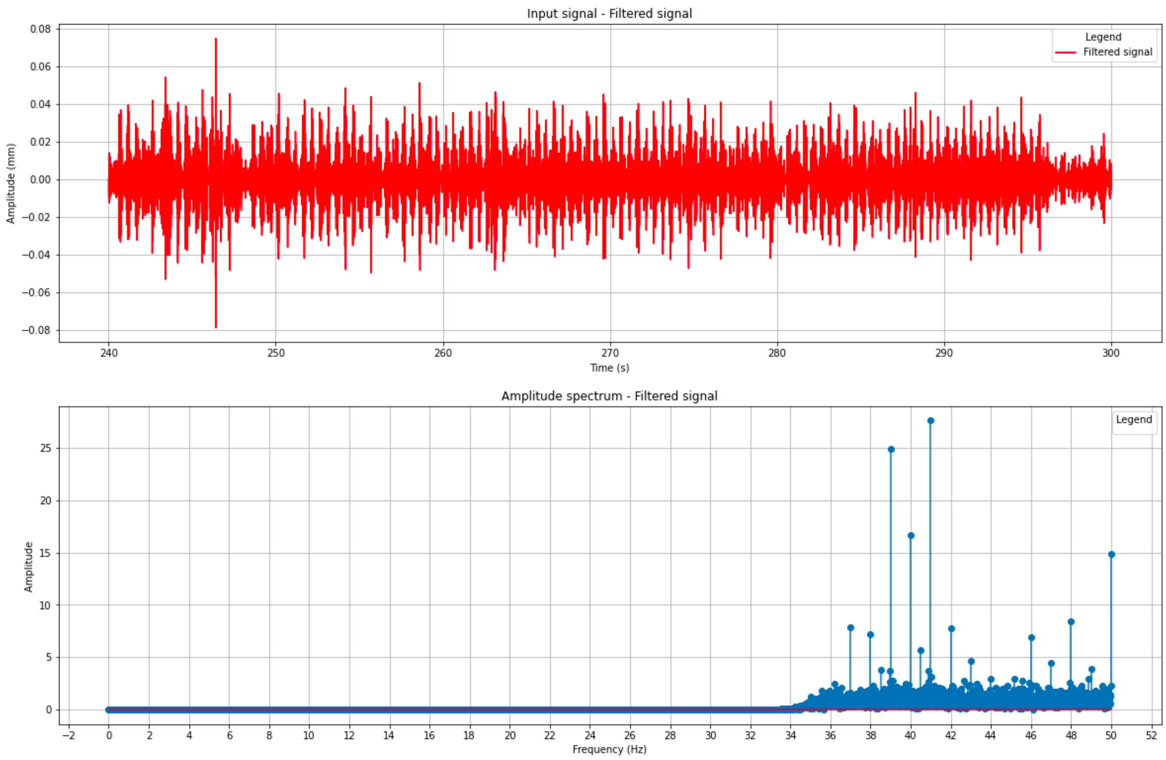

Figure 6.(2) Part = EDM, Signal and Spectrogram for X-axis movement after applying filter

When I saw those plots I got a hypothesis that it should correlate somehow with the BPS of music. Because now we can see some pattern in the time series which is evenly distributed through the time.

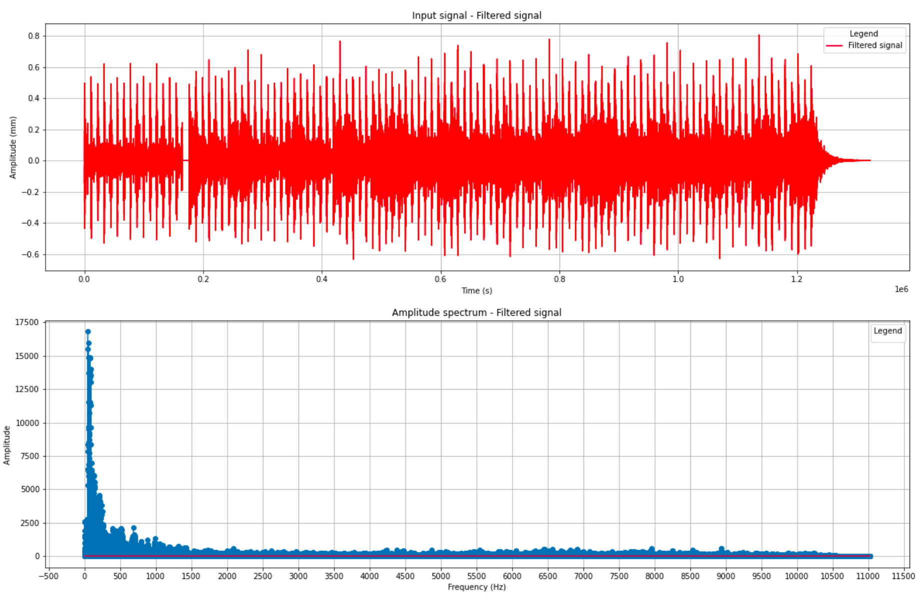

Figure 9. Raw sound signal and Amplitude Spectrum - EDM Sound

For both those signals (movement and sound) there is a high Amplitude amount of quite the same frequency windows (~35 Hz - 60Hz).

After finding EDM **tempo** = **117.4** Bps, let's plot them:

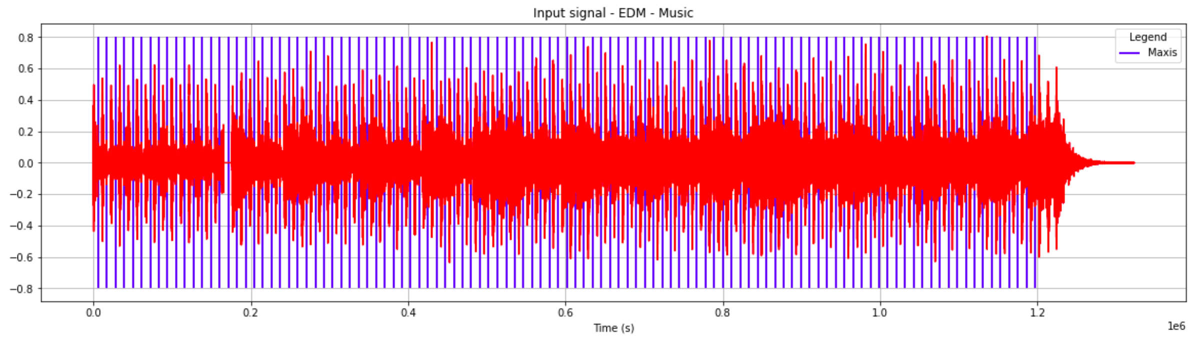

Figure 10.1 Raw sound signal with Beat Frames - EDM Sound

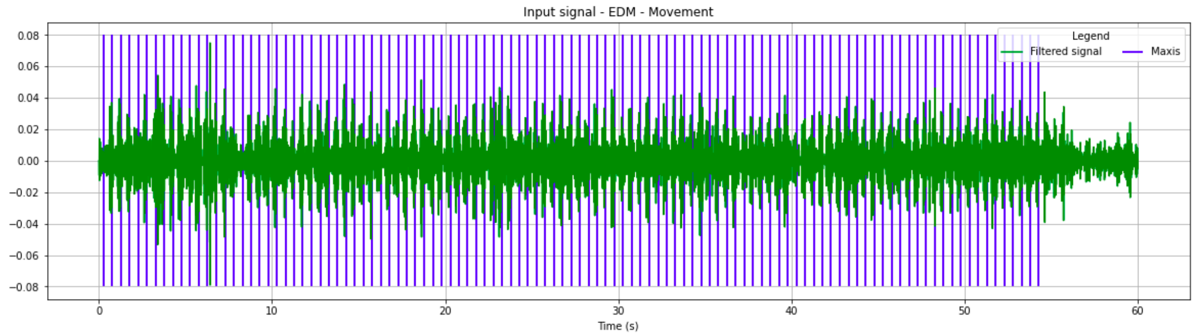

Figure 10.2 Filtered movement signal with Beat Frames for Sound - EDM Movement (X-axis)

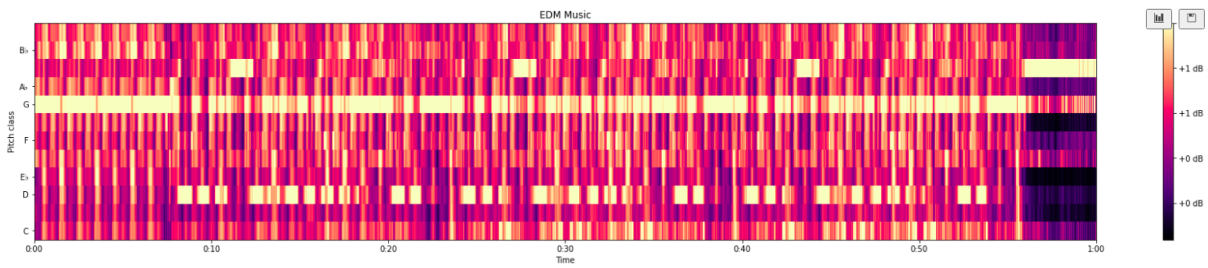

Figure 10.3 Spectrogram (STFT) for EDM Sound Signal

This set of observations confirms that for this EDM signal and movement data there is high relation between each other. From finding some eye-catching frequencies in movement data, we find out that sound signal has the same window of 'main' frequencies.

The fact that beat frames from sound accurately fit the highest peaks of the movement filtered data, even more, convinces the hypothesis that each type of music (or its features, which were not considered in this work) makes a different influence on how our body reacts to it.

And all of this is just a little piece of cake of '**micromovements** vs **sounds'** because there is a lot to investigate and develop. But it is enough to say "Yes, it works. Let's go deeper!"

4 Conclusions and ideas for improvements

The goals set as the main direction of this project were achieved: getting to know with such signal types combination, finding some relations between unconscious movements and sounds, exploring the features, and even getting some statistical results. That is a good start to continue developing this project.

What can be done more:

- Find more ways to correlate different movements between each other
- Explore more sound features to find correlations with movement (not only frequency and Bps as for EDM example in this paper)
- Write classification and predictive models to definitely approve all concepts and hypothesis
- Get EEG information for similar experiment to not only know how human reacts to some stimuli but also research why it happens in the brain
- And a lot of new bright ideas!

Resources:

1. Jensenius, Alexander Refsum (2021). Best versus Good Enough Practices for Open Music Research. Empirical Musicology Review. ISSN 1559-5749. 16(1).

2. Zelechowska, Agata; Gonzalez-Sanchez, Victor E.; Laeng, Bruno & Jensenius, Alexander Refsum (2020). Headphones or Speakers? An Exploratory Study of Their Effects on Spontaneous Body Movement to Rhythmic Music

3. Motion capture studies of action-sound couplings in sonic interaction - STSM COST Action SID report Jensenius, Alexander Refsum (Research report / Forskningsrapport, 2009)

4. Zelechowska, Agata; Gonzalez Sanchez, Victor Evaristo; Laeng, Bruno; Vuoskoski, Jonna Katariina & Jensenius, Alexander Refsum (2020). Who Moves to Music? Empathic Concern Predicts Spontaneous Movement Responses to Rhythm and Music. Music & Science.

5. Bruderlin, Armin & Williams, Lance. (1995). Motion Signal Processing. Proceedings of ACM SIGGRAPH 1995. 10.1145/218380.218421.

6. Godoy, R. I. and M. Leman (Eds.) (2010). Musical Gestures: Sound, Movement, and Meaning. New York: Routledge.