Major Project

Conception of New Rhythm-Based Dexterity Training Methods with Adaptive Mechanics and AI

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Munich, 4th of March 2022.

Place and date | Signature of student

Written by Yann Savard

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4th of March 2022

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Conception of New Rhythm-Based Dexterity Training Methods with Adaptive Mechanics and AI

Abstract: This project is a proof of concept that aimed at generating new rhythmic training methods (RTM) and comparing them with conventional ones used by professional musicians. Three processes were used: self-monitoring of performance, adaptive mechanics and artificial intelligence techniques from deep learning. An adaptive rhythmic training application (ARTA), which is research tool, was designed and programmed during this project for its purposes. Three different 10 days trainings sessions were made with a total of 5 participants (1, 4, and 4 participants, respectively) who at least had piano and/or percussion training at any point in their life. A methodology was developed to optimize RTM with artificial intelligence (AI) that was trained to predict human keyboard typing performance associated with specific rhythmic patterns. The first training was made with the self-monitoring process for the calibration of the adaptive mechanics and the generation of data for the AI (a bilateral LSTM neural network, and the two other evaluation trainings were designed to compare the new rhythmic patterns discovered through the methodology of this project with conventional methods. The involved 144 trials in total, with an average of 4 trials per day for each participant, for a total of 10 days. The results showed that despite the fact that the new rhythmic patterns were more complex to learn and execute, some of them were found in the top 50 of all the patterns performed during the 10 days with the best performance and speed performed during the whole training, at least one part out of the four implemented series of new rhythmic patterns in the last evaluation training proved to be better the a conventional RTM for the group of 4 participants and for at least one participant, the whole daily program implemented with new patterns allowed this person's to attain a better performance than for the 2 conventional RTM implemented. These results suggest on one part, that the intentional generation of theta brain waves during the performance of a task is associated with better learning performance for the practiced tasks but also that the methodology explained in this project is a valid research and application approach to discover new rhythmic pattern that could help in the learning of motor skills in general.

Chapter 1

1.1 Presentation of the major project

Music training offers different techniques to methodically improve precision and timing of musical performance and some of them are well established and used by professional musicians across the world. They allow complex sequences of coordinated muscular movements to be executed effortlessly at high speeds. This project is a proof of concept that aims at conceiving new evaluating rhythmic training methods (RTM) and evaluating them in comparison to conventional ones. This will be done with the help of a rhythmic training application that will be designed and programmed for the purposes of this project. My hypothesis that lies behind this proof of concept is that the performance of many forms of motor and cognitive tasks can be enhanced through RTM. It is already used in many fields, but could be used in many other ways, to make the learning of new abilities more efficient.

A particularity of this project is the use of musical training techniques to develop a skill that normally does not involve musical elements: keyboard typing. The relevance of discovering new RTM is that it could optimize the learning efficiency, not only for typewriting, but more broadly for motor dexterity tasks like musical performance and sports. Furthermore, cognitive tasks such as inner and outer speech articulation exercises could also benefit of more efficient rhythmic training, which could have a significant impact on verbal working memory (WM), due to the importance of the speed of articulation in verbal WM performance that have been shown in previous research. (Ding, Gray, Forrence et al., 2018, p.12)

To discover whether or not it is possible to generate new RTM that are more efficient than conventional ones with the methodology that will be developed in this project, three different processes will be used: self-monitoring of personal performance, adaptive mechanics and artificial intelligence (AI), with deep learning techniques for artificial neural networks (ANN).

1.2 Goal definition

Goal priority legend: Must have (M), Should have (S), Could have (C)

1.2.1 Adaptive Rhythmic Training Application (ARTA)

(M) Design of the ARTA.

1.2.2 Adaptive mechanic

1. (M) Implementation of an adaptive mechanic based on the results of a first 10 days training (section 1.2.5 – point 1)

2. (M) Analysis of the results of training 1 (section 1.2.5 – point 1) and 1st conception of a new RTM according to them.

1.2.3 Research about AI – Deep learning techniques

1. (M) Research of AI techniques relevant for the project.
2. (M) Generation of a data set with training performance data to train the ANN (at least 10 000 input data)
3. (M) Conception, implementation and a 1st training of an ANN with the data generated through training.
4. (S) 2nd training of an ANN with the new data with the same technique(s) as before or differently if necessary.
5. (M) 2nd conception of a RTM: If the results show regular rhythmic patterns, I will conceive a new RTM according to the ANN's results.

1.2.4 Research about human learning performance

(M) Research in different fields in order to gain deeper and broader understanding of rhythmic training for the design of the ARTA.

1.2.5 Evaluation of performance and RTM with the ARTA

1. (M) Training 1 - Evaluation of my own performance with adaptive parameters and generation of data for the ANN.

2. (M) Training 2 - Evaluation of the efficiency of all RTM with a comparative experiment, with at participants.

1.2.6 Other goals:

1. (M) Get Regular feedback from supervisor and help from others.
2. (C) Generate more RTM then planned if possible.

1.2.7 The outcome of this project:

The important written aspects in this major project will be:

1. A description of the conception of the ARTA, its features and important aspects of the program will be made: The self-monitoring aspects (all graphics), the adaptive game mechanics and the deep learning technique(s) used to develop the neural network (A.I.) will be described.
2. The different 10 days trainings with the ARTA will be described and their results will be analysed in chapter 4 and 5.
3. The description of the new RTM, hopefully better than conventional ones, conceived through this project will also be presented.
4. The assessment of this proof of concept: whether the methodology developed through this project was successful or not in generating new RTM which are better than then conventional ones.

1.3 Relevance of the idea in the industry

1.3.1 Fields of relevance

Rhythmic exercises are widely used in many fields. Here are examples where they are relevant:

1. Gaming industry (beat games in particular);

2. Computer science (fields of artificial intelligence)
3. Performing arts like music, theatre and circus;
4. Education;
5. Medical fields (music therapy, physical rehabilitation, logopedics, psychology and neuroscience);
6. Sports.

Importantly, the new RTM could be implemented in future applications like games, educational or rehabilitation software. Other products related to rhythmic training in the above-mentioned fields could also benefit from new methods. The process that allows their generation explained in this project could serve for future development of RTM with more financial resources.

1.3.2 Target group:

People who with interest to improve their keyboard typing skills, musical skills, performance at motor skills (sports, performance arts, etc.), game designers, software developers in the above-mentioned fields, therapists, researchers in fields related to this project. This project can be published on different online academic libraries and be available for future research.

Chapter 2 – Context

2.1 Conception of the adaptive rhythmic training application (ARTA)

2.2.1 Professional musicians and rhythmic exploration

There is already literature about the efficiency of rhythmic training in complex motor tasks in the field of music. According to a research involving

27 pianists whose activity of the intrinsic hand muscles were recorded and analysed during piano practice, Furuya and colleagues discovered that using different rhythms allows the muscles to

cooperate in different ways and the nervous system to relax other muscles irrelevant to the task and lead to a better performance. (Furuya, Shinichi, and Sayuri, 2018)

2.2.1.1 Tempo progression patterns

Here in **figure 1** are two tempo progression patterns commonly used by musicians to build up precision and speed in musical performance:

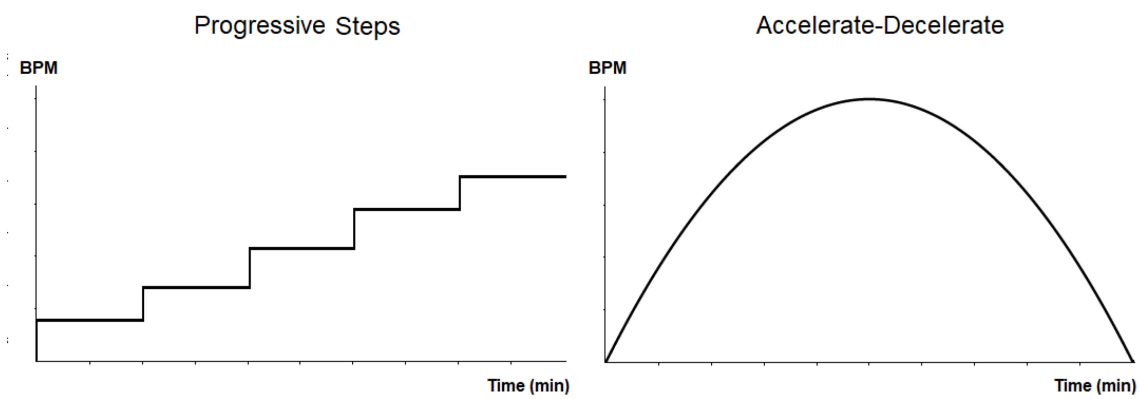


Figure 1: Conventional tempo progression patterns

Left (Fig. 1): A musical section is practiced at a stable tempo, starting slowly and progressively increasing the tempo by steps of a certain value, for example, 5 BPM. A very well know example of this practice are the *Virtuoso Pianist* exercises, from Hanon. (Bokão, G, 2022).

Right (Fig. 1): This is a tempo progression often used for rudiments practice (Percussive Arts Society's International Drum Rudiments) in percussions. A rudiment (rhythmic pattern) is executed very slowly at the beginning with the movement exaggerated and the tempo increases regularly and progressively until the execution loses stability, or a mistake is made. The speed than starts decreasing progressively back to the initial speed. (Percussive Arts Society, 2022)

2.2.1.2 Rhythmic patterns

Here are two sets of conventional RTM, followed by interesting facts about Mozart’s rhythms:

1. A doctoral study of Wallick describes practices and techniques commonly used by concert pianists mentioned the following practices (Wallick, 2013, p.91-101):

    - Hands separate
    - Rhythm practice;
    - Using a metronome;
    - Slow practice;
    - Playing through.

2. One of them described a rhythm practice, which consists in breaking a musical section into 3, 4 or 5 notes, accentuating the first, then the second, third and lastly the fourth (Wallick, 2013, p.96-98). This permutation of accents was also thought to me 23 years ago when I started to play piano by a music student who had learned the same method and used it not only with a grouping of 3 to 5 notes, but also for from groupings of 2 to 8 or even more.

    Another type of rhythmic patterns is described by pianist Josh Wright, doctor of musical arts and pianist, where notes and played softly and consecutively up to the last note, which is accentuated and a pause is made on that note. The length of the note sequences can vary from 1 to 17, increasing progressively in size. (Wright, 2019)

- **Rhythms in Mozart's music:** When it comes to musical performance, it is commonly known that Mozart had exceptional skills and could play a whole musical piece after hearing it just once. Xing and colleagues investigated the "Mozart effect" on cognitive performance of rats and undergraduate students in different tasks while exposing them to Mozart's Sonata K-448 for two pianos and observed the following:

    > "Our results first indicated that the rhythm of Mozart music produces similar effect as Mozart music, but the pitch of Mozart music does not. These facts confirmed the crucial importance of rhythm in music and its major role in the Mozart effect." (Xing, Yingshou, Yang Xia et al., 2016)

2.2.2 References for the ARTA:

Guitar Hero: a similar game mechanic as in Guitar Hero will be used, where the keys to press are visually represented in such way, that they come from the top to the bottom of the scream, making it clear for the player, when exactly the need to be pressed.

Figure 2: Guitare Hero 3 (GameSpot., 2021)

SpeedCoder - Typing training program:

a) SpeedCoder is one of the typing training software available online, where a person can type while directly looking at a written code text are seen in real time when a mistake was made. The character that was mistaken appears in red. The ARTA will have a similar disposition of the text.

b) When a practice session is over, statistics of the session can be seen, including the typing speed in words per minute, the accuracy and a list of the keys that were missed is shown. The ARTA will have similar statistics.

Figure 3: Training Session (C Sharp Program Typing Practice | SpeedCoder, 2021)

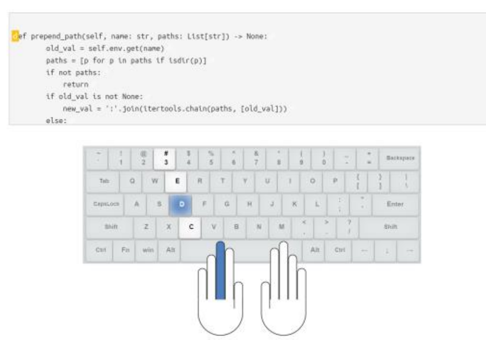


Figure 4: Lesson Summary (C Sharp Program Typing Practice | SpeedCoder, 2021)

Mindfield Biosystems Mindmaster 4 neurofeedback software: This software is designed to self-monitor neurofeedback in real-time. The brain waves activity can be observed in real-time with graphics updating in real-time. The values have three different time spans: 0.1 seconds, 0.3 seconds average and 0.1 minutes average.

Figure 5: Mindfield Biosystems Mindmaster 4 neurofeedback software's interface (Mindfield Biosystems Ltd., 2021)

2.2.3 Self-monitoring process for typing training and evaluation of the performance

For the purpose of improving juggling performance, Dr. Efrat Furst, neuroscientist, and Mickey Choma, a former fencing champion and professional juggler proposed a self-monitoring method to children who recorded their juggling performance through time in order to find out by themselves which practice strategies are the most efficient for them. (Furst, Chroma, 2014) Here is a screenshot of the graphical representation that they used:

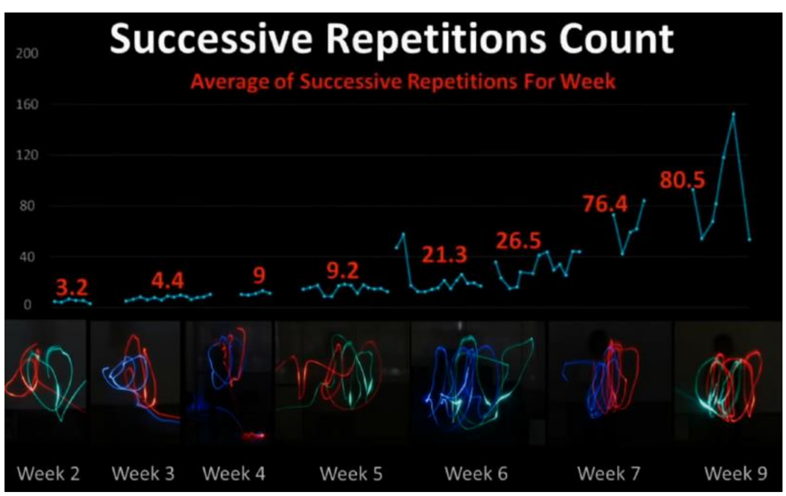


Figure 6: Screen shot of the self-monitoring method presented by Furst and Choma (Furst, Choma, 2014)

2.2 Adaptive game mechanics

2.2.1 The state of "flow" during a task - Above boredom and below frustration

A key aspect of gamification of exercises is to allow the player to experience pleasure while practicing, without it hindering the performance, or learning goals. One important type of pleasures experienced during a game or a task is the experience of "flow", which can have many meanings. Lindley and colleagues, hypothesize that this state:

"...is associated with attentional demand, in particular occurring when schema execution demands attentional resources above a level that would result in player boredom and below a level that would result in excessive difficulty and consequent frustration" (Lindley, Craig A., und Charlotte C. Sennersten, 2008).

2.2.2 The optimal difficulty level for performance

Adaptive mechanics allow games to be adapted to the abilities of the player in real-time. The level of difficulty of a game, or task, can be calibrated with dynamic difficulty adaptation (DDA): "DDA is based on the mathematical analysis of structures and relationships within a game system" (Tremblay, Jonathan, Bruno Bouchard, 2010). Adaptive mechanics precisely calibrate parameter values in a game to generate the best conditions to the player be optimally challenged at all time.

2.3 Research about AI – Deep learning techniques

2.3.1 Structure of neural networks (ANN)

The concept of neural networks has been taken from biological neural networks. They constitute of artificial neurons (nodes). Each neuron can be activated when its numeral value reaches a certain threshold and are adjusted through their weights and biases parameters, in consideration of the surrounding neurons activation levels. Neurons are usually structured in different layers, also called hidden layers (Kandpal, 2018), of the neural network. The figure 7 depicts the structure of a recurrent neural network, an ANN type used to predict time series. (Kandpal,

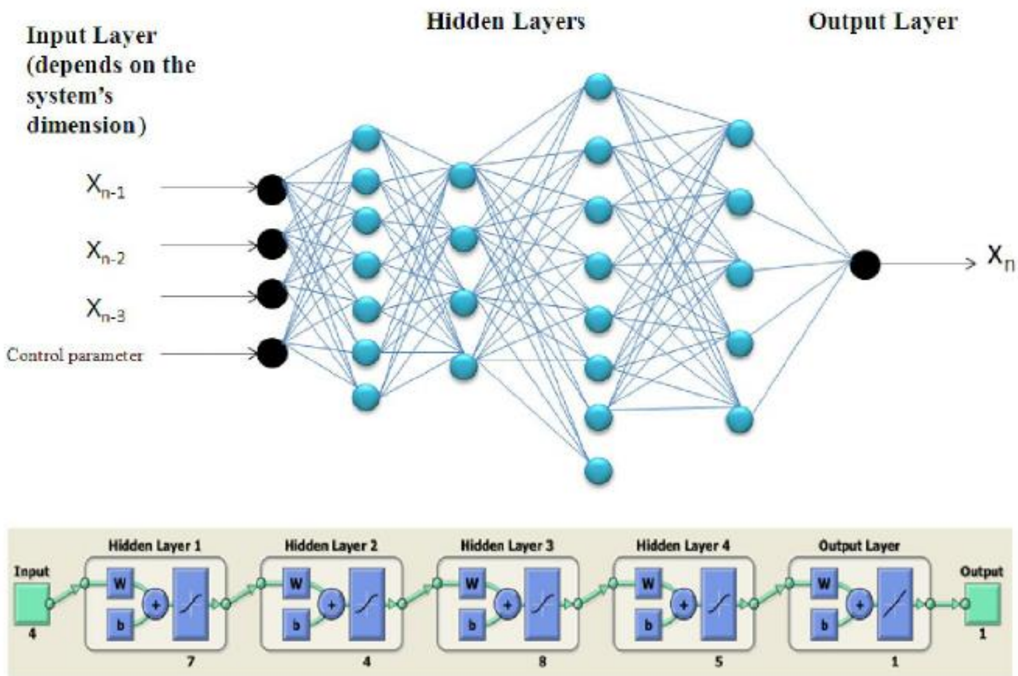


Figure 7: Recurrent Neural Network (Kandpal, 2018)

2018) Originally, "[the] main purpose of ANN was to solves problems as the human mind does" (Sharma, 2020) and eventually, the focus diverged from biology and was set more on the execution of certain tasks. (Sharma, 2020)

2.3.2 Supervised learning

Without prior knowledge of a task, such as the classification of images or the prediction of a series of events occurring gradually in time, a neural network receives a set of input data (in form of images, vectors, arrays, etc.), and is trained to calculate a function that led to pre-defined outputs, like the classification of a specific animal present in the image or a floating coma number between 0.0 and 1.0. The results of that are calculated are compared to the actual outputs and the function is updated to match them as precisely as possible. (Sharma, 2020)

2.3.3 Types of neural networks:

2.3.3.1 Convolution Neural Network

Convolutional Neural networks are used for image recognition tasks:

They include Convolution layers, Max pooling layers, fully connected and the desired output layers. They are used to classify images. While the Convolutional layers are used to extract specific features of the images (like curves, points and various patterns) at different levels, the Max Pooling layers samples down the input images. Figure 8 is an example of the structure of CNN. (Wagh, Dr Abhay E., 2021)

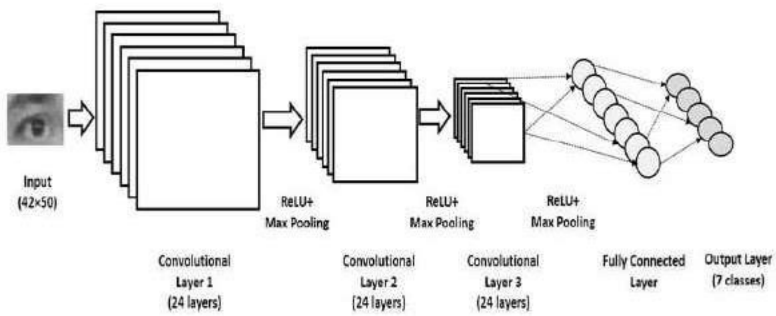


Figure 8 Architecture of Convolutional Neural Network (CNN) (Wagh, Dr Abhay E., 2021, p.1213)

2.3.3.2 Long short-term memory (LTSM) and bidirectional LSTM neural networks

LSTM "is a Recurrent Neural Network (RNN) architecture that uses feedback connections that allow it to solve many kinds of general computing problem. They excel at classification and forecasting for time-series data" (Valles, 2019, p.194) It is commonly used to forecast values and/or events such as the weather" (Ghosh, 2018).

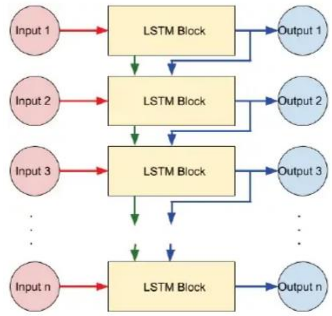


Figure 9: Figure 10: RNN-LSTM Architecture (Valles, 2019, p.194)

The layers are organized into blocks that can store new information, keep already existing one and forget other. A variation of this type is the bidirectional LSTM (BLTSM), which work exactly the same way, but they include two layers of LSTM: the first one taking the data in a forward direction (chronologically) and the other one, backward. This process adds "additional context to the network and result in faster and even fuller learning on the problem" (Ghosh, 2018).

2.3.3.2 Prediction of human performance with artificial neural network

Brownlee used an LSTM to predict his performance playing the rhythm game OSU. He saved his performance of many years of playing the game and identified relevant parameters to predict his performance, such as the time and the coordinates of his mouse in a chronological order. He than reshaped organized his data in form of time windows, including recorded values starting 4 steps before the current time, up to 2 steps after. (Jevnik, 2018)

time	x	y
00:37.366	372	94
00:37.763	447	205
00:38.027	217	299
00:38.291	229	171
00:38.424	274	358
00:38.688	149	221
00:38.952	330	186
00:39.217	233	127
00:39.481	233	127
00:39.613	198	303

Figure 11: screen shot - time windows data shape (Jevnik, 2018)

2.4 Research about human learning performance

2.4.1 Music therapy and neuroplasticity

Rhythmic stimulation is used in rehabilitation of Parkinson disease, to help patients walk fluidly. Rhythmic stimulation can literally re-energize injured parts of the brain and through neuroplasticity, help patients to recovered the ability to walk fluidly. (Stegemöller, 2017).

2.4.2 Neuroscience - Theta brain waves and auditory memory performance

A post doctorate study of the Montreal Neurological Institute and Hospital about the influence of rhythmic fluctuations on brain activity and behaviour demonstrates that the presence of theta waves during an auditory memory retention task can specifically improve auditory working memory performance. One of the researchers said in an interview that "the more theta waves the brain is generating during this retention period, the better are the participants at doing the task" (Cell Press, 2021) (Albouy, Weiss, Baillet et al., 2017)

2.4.3 EEG experiment – Intentional generation of theta brain waves

For the purposes of this project, I investigated a technique that I developed while researching about the effects of rhythm on the brain. For years I have been carefully observing the effects of temporal exploration during music exercises, sports, juggling, speech articulation exercises and general attentional focus exercises. I noticed that they created a relaxing and focusing effect that suddenly made the execution of a task easier. As an outcome of many years of experience with this subject, I developed the Zoom-in technique.

Figure 12: Yann Savard, during the EEG experiment

Figure 13: Photo of the EEG interface

Thanks to my wife Astrid Savard, the therapy centre Therapiezentrum Grafing/Ebersberg and occupational therapist Rebekka Kropp who helped me to realize this experiment with professional EEG material, we could observe that high levels of theta brain waves (up to 44 μV) were generated simply by shifting covert attention in specific ways. We recorded on video the neurofeedback interface to see the effects of changing attentional focus from the left to the right thumb tips or from the left thumb tip to the right big toe tip. The attention was "zoomed-in" (narrowing the focus to be briefly stilled in the sensations of fingers or toes tips) in different rhythmic patterns at various tempos. The EEG sensors were placed at the junction of the frontal and parietal lobes, areas associated with attentional control (Kropp, 2021). We measured the following brain waves: theta, associated with meditation states (UCI Open, 2021) and has positive effects on the working memory performance (Cell Press, 2021); alpha 2, also related to relaxation (UCI Open, 2021); and beta waves, related to high frequencies like motor activities (UCI Open, 2021) and stress manifestations (Kropp, 2021). The experiment can be found in Annex 1.

The Zoom-in technique: The attention starts focusing (observing normally) on point A and moves rapidly to point B, where the attention is "zoomed-in" as narrow as possible into that point. The two points can be anywhere the attention can be focused on in the physical space and the attention can alternate from point to point, as long as the last point is focused on with zoomed-in attention, a peak of theta brain waves will be generated automatically. The following image illustrates these steps.

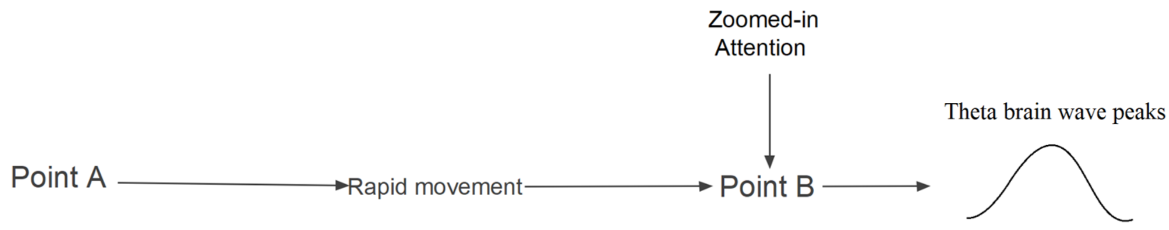


Figure 15: Zoom-in technique

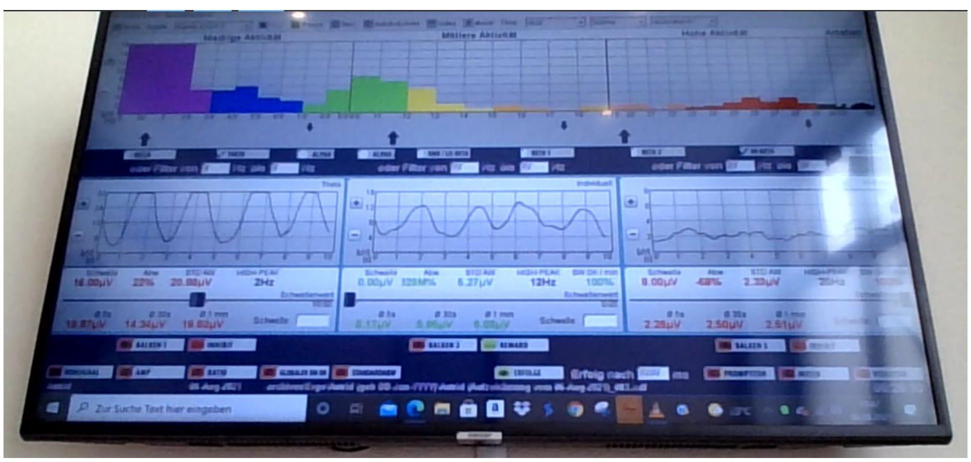


Figure 14: Exercise 12 of the EEG experiment in annex 1

The effect of a single execution of this technique is the generation of a theta brain wave peak. When this is done regularly in a cyclic rhythmic pattern, high levels of coherent theta brain waves can be generated. The following images shows the results of exercise no. 12 of the experiment, where the attention was alternating from the tips of the left thumb to the right big toe (hallux) at 50 beat per minute (BPM), synchronized to a metronome sound, and the rhythmic pattern was 2/2 (soft attention on the right thumb – zoomed-in attention on the left big toe):

2.5 Evaluation of the RTM - One-group pretest–posttest design

Here is the definition of a form of comparative experiment that requires only one group, it is called one-group pretest–posttest:

> "[...] a variation of the pretest–posttest design in which only a single set of participants is measured on a dependent variable of interest, exposed to a treatment or intervention, and then measured again to determine the change or difference between the initial (pre-) and second (post-) measurement" (American Psychological Association, 2020).

It is important to mention that the lack of control group in this form of experiment "makes it difficult to attribute gains in the posttest score to the intervention, as other elements [...] may have contributed to any change observed" (American Psychological Association, 2020).

Chapter 3 – Method

Goal priority legend: Must have (M), Should have (S), Could have (C)

The following sections constitute the methodology that will be used in this project.

3.1 Adaptive Rhythmic Training Application (ARTA)

The ARTA will be designed, conceived and used for the purpose of evaluating, optimizing and/or generating new RTM. The programming of the ARTA will be done in parallel to this project, as the Advanced Specialized Project of my bachelor program, but important elements of the program will be described in chapter 4.

The ARTA should have the elements that follow.

1. A graphical interface that allows people to train with various RTM.

   Reason: To make the game mechanic interesting, intuitive and easy to use, features of the popular rhythm-based videogame *Guitar Hero 3* (section 2.2.2 – no. 1) will be created: the text characters that should be pressed will move downwards in a top-down direction, up to a specific place where they should be pressed in precisely in a metronome tempo. Also, a similar text disposition of a conventional keyboard typing training program - *SpeedCoder* (section 2.2.2 – no. 2) - will be designed and implemented.

2. Features for self-monitoring of performance in real-time.

   Reason: Real-time graphics are used for EEG neuro-feedback in software like Mindfield Biosystems' *Mindmaster 4* (section 2.2.2) to allow a person to receivedirect feedback of the actions that they take. Based on this example, similar graphics with be implemented in the ARTA. Another possibility to analyse performance over time are static graphics displaying the whole training performance. Such graphics will also be implemented to have a good overview of the participants' performance. This methodology is inspired by the works of Furst and Choma (section 2.2.3).

   An adaptive mechanic with dynamic difficulty adaptation (DDA) with parameters that can be changed in real-time by the participants in the first place will be implemented and its parameters will then be calculated with fixed calculated values. Adaptive parameters will be visible in the graphical interface in the form of graphics or other UI elements and will be adaptable in real-time.

   Reason: To allow participants to train with an effective level of challenge, DDA will be implemented (see section 2.3.1) with parameters that can be modified in real-time by participants, so that they can find out through their own experience which training conditions (parameter values) lead them to the best performance.

5. A section for the AI including a neural network and all that is required to use it.

   Reason: This section will be dedicated to the AI that will optimize the RTM according to the results of the AI techniques to be discovered in section 1.2.5.

6. A section for the evaluation of the 10 days training to be conceived in section 1.2.6 (point 2).

   Reason: In order to evaluate the efficiency of the new RTM, a section of the ARTA has to be dedicated for the manipulation of data and the generation of static graphics that compare conventional and new RTM. A part of this point will be the implementation of an evaluation method for the context of this project based, a form of *one-group pretest–posttest* comparative experiment (see section 2.5.1) adapted for this project, giving that the resources available for it are limited to what I can give financially to participants and their availability.

7. A structure for the management of performance files of the participants.

   Reason: Ideally, the performance data of participants could be sent automatically to a database like MongoDB (Kiedrowski, D. 2021) for me to access easily, but other solutions that make the manipulation of file easy to handle would also be good.

3.2 Adaptive mechanic

1. Implementation of an adaptive mechanic based on my results of the first training (section 1.2.5 – point 1) that should allow persons training with the program to be efficiently challenged with parameters tuned in real-time to their performance, so that the challenge is gradually increasing with the performance.

Reason: In tempo progressions of conventional RTM methods (section 2.2.1.1), the speed at which the tempo should be changed is usually not measured by a computer in real-time and the musicians have to monitor their progress intuitively, with their attention. A DDA can be implemented to calibrate the tempo very precisely to give a person optimal training conditions to obtain the best results for the time practiced.

2. Analysis of the results of training 1 (section 1.2.5 – point 1) and 1st conception of a new RTM according to them. Here, the tempo progression pattern will be in focus.

3.3 Research about AI – Deep learning techniques

1. Research of AI techniques relevant for the project:

   Reason: I need to research and learn about the field of machine learning to find relevant methods suitable to develop an AI that can lead to the optimization of conventional RTM.

2. Training performance data generation: I will do a 10 days training with the ARTA to generate data to train the ANN and possibly organize a tournament with a few persons.

   Reason: The main goal here is to generate at least 10 000 input data to train the neural network. This is an average number required for machine learning (Paul, 2021)

3. Conception, implementation and training of an ANN with the data generated through training. The training method for the ANN will be established according to the research in section 1.2.1.

   Reason: The implementation of the ANN and its components is the central aspect of the artificial intelligence, which is the third process of this project.

4. 2nd training of the ANN with the new data with the same technique(s) as before or differently if necessary. Also, a 10 days training of approx. 20 minutes per day over 2 weeks.

   Reason: A second training with the new data generated from the training/tournament (point 2) would allow the ANN's predictions results to be potentially better suited for a wider range of persons.

5. 2nd conception of a RTM: If the data shows a regular pattern, I will conceive new RTM according to the ANN's results.

   Reason: There is a chance that some RTM could be better than others and the best ones could be identified.

3.4 Research about human learning performance

1. Research in different fields:

   Reason: Through this research, deeper and broader understanding of rhythmic training can be acquired. This new knowledge will influence the design of the ARTA and/or the machine learning training methodology. This will help, to find out relevant features and parameters that should be added in the program. The findings will be documented in chapter 2.

3.5 Evaluation of performance and RTM with the ARTA

1. (M) Training 1 - Evaluation of my own performance with adaptive parameters and generation of data for the ANN: I will self-monitor my progress, changing parameters in real time and the performance data will be saved in a folder. (C) I could ask others if they are willing to do the same trainings.

   Reason: The main purpose of this part is to be able, after this training, to calculate the parameters of the adaptive mechanics to allow an optimal performance to be achieved by participants when training with rhythmic patterns in Training 2.

   (M) Training 2 - Evaluation of the efficiency of all methods with a comparative experiment: I will implement an evaluation mode in the ARTA to compare conventional and newly generated RTM in another 10 days training program. The efficiency of all methods will be compared using the performance graphics. (S) I should ask other people if they would like to do the same training. Within the realms of this project, I will invest a lot of efforts in designing this experiment and invest personal financial resources for the participants do to obtain results that are as valid and accurate as possible. It is important to mention here, that future research under more controlled conditions should be made to be able to examine the results with greater accuracy.

   Reason: To test the efficiency of the new RTM compared to conventional ones for different people, including myself.

   (Both trainings will involve approximately 20 minutes per day (Klingberg, Forssberg, and Westerberg, 2002), they will involve 10 sessions over 2 weeks.

3.6 Other goals:

1) (M) Feedback from supervisor and help from others: I will regularly get feedback from people and ask for help if needed. I will also show my progress to a supervisor regularly.

   Reason: This will allow the project to be enriched with suggestions and comments.

2) (C) If it is possible to make more than two RTM conceptions phases, I could do this.

   Reason: The same reason mentioned in section 3.3 – point 5)

Chapter 4 – Execution of the project

4.1 Adaptive Rhythmic Training Application (ARTA)

Description of the ARTA and how it will be used in this project

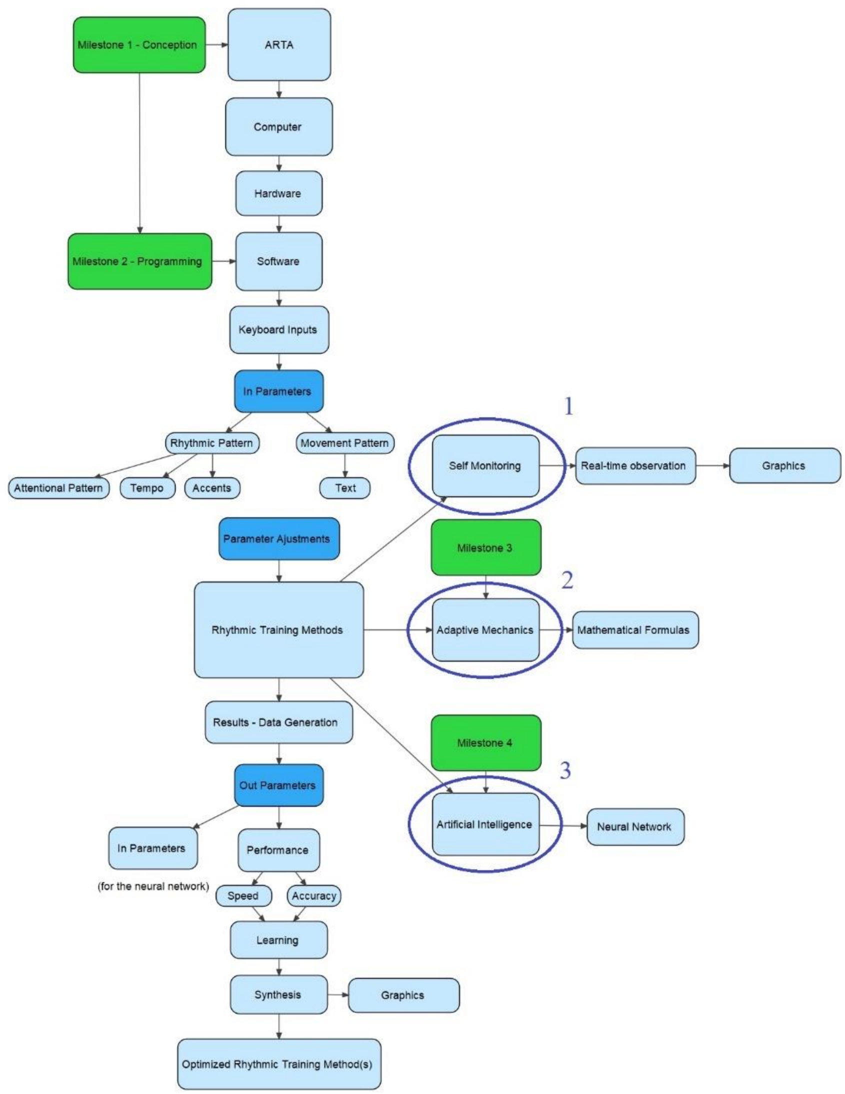


Figure 16: Mind map of the ARTA and how it will be used

In one sentence, the purpose of the ARTA is to help generate new optimized RTM with the use of self-monitoring, adaptive game mechanics and AI, and to compare their efficiency with conventional RTM.

It is designed to be to used as self-monitoring program that records and displays the training progress in real-time, to allow the player to manage tempo related parameters to find-out by themselves what the best tempo progression is for them.

Graphical interface:

Here are the main components of the graphical interface that was created:

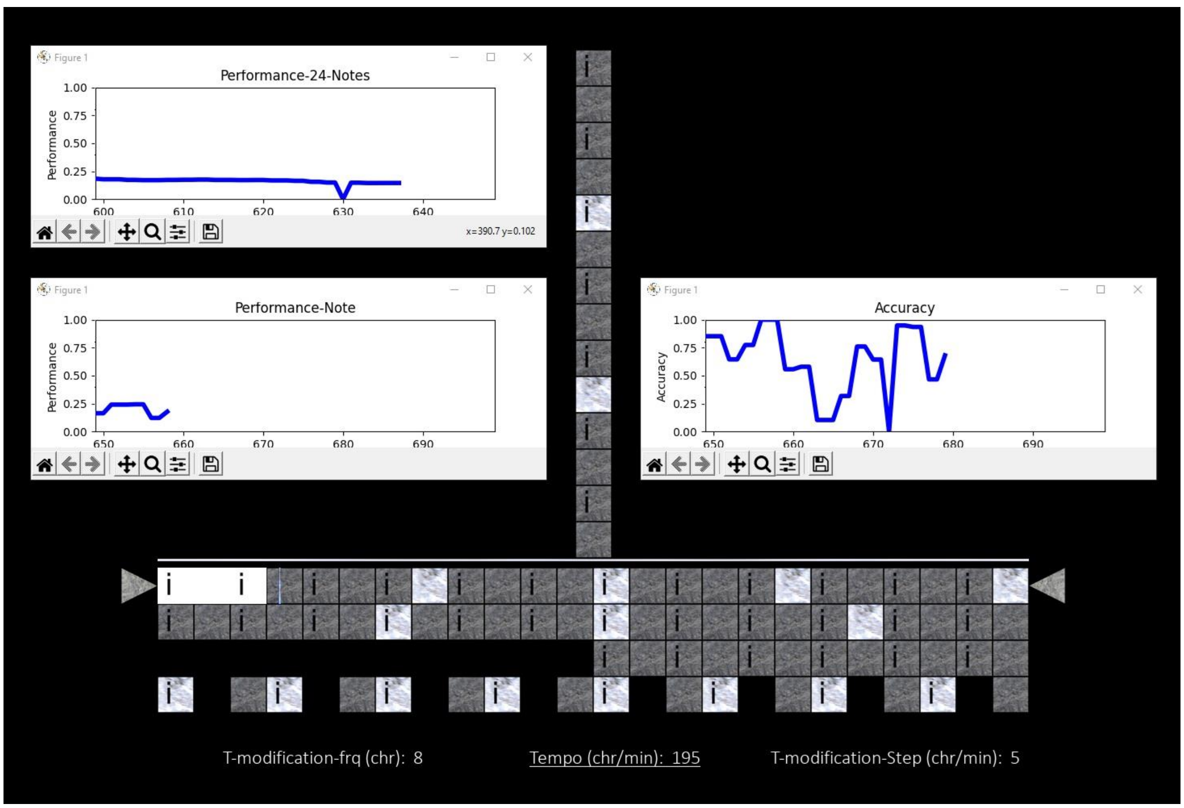


Figure 17: Screen-shot of the graphical interface of the ARTA

Live graphics were implemented using the Python matplotlib package to show performance and accuracy values in real-time, as part of the self-monitoring process, (section 2.2.3) with the help of a tutorial by Sentdex (sentdex, 2015). I received the feedback from my supervisor, that

I should use multi-threading to manage the animated graphic windows (figures). Since in Python 3 language, these figures are already executed on a multi-threading basis, I had to use multi-processing to synchronize them with the main Pygame window. I found this quite challenging to manage the focus of the windows and decided to invest time to make them functional, but they are not completely user friendly, because at the beginning of each round, the background has to be clicked to avoid that the focus of the program gets on them instead of the Pygame window that controls the keyboard inputs. I had to explain this to all participants of trainings 2 and 3 and once they understood this, they could do their training properly.

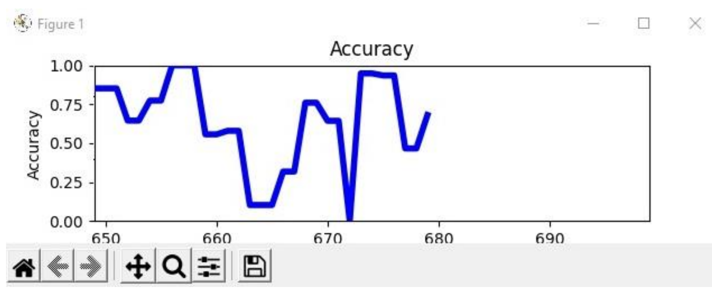


Figure 18: live performance graphic (accuracy parameter)

The vertical text characters column int the middle is where the runits move at tempo speed from top to bottom of the screen until they reach the white line, where they disappear at the exact moment when this character should be pressed. This is the game mechanic similar to the game Guitar Hero. This helps the player at the beginning to get used to press on the beat.

The horizontal text character's part is a section of 24 x 4 squares with a written text character at the centre, which is placed in a way that they can be read from left to right as conventional text (in European languages). For this point, I received feedback during a presentation before the class and the suggestions were made that I add a line exactly where the characters should be pressed and a small space between the text characters in both horizontal and vertical sections.

The needle travels at tempo speed from left to right in the horizontal text part a reading guide, to help the player to stay on tempo, while keeping the eyes on this text part. This needle was not planned and I added it later-on as an extra help to allow the eyes to focus more easily on the horizontal part, without having to constantly look up to the vertical one.

The adaptive mechanic tempo-related parameters can be modified in real-time by the player with the arrow keys: left and right keys to select the parameters; up and down to increase and decrease their values. They can be seen at the bottom of the interface as white text and the parameter that can presently actively be controlled with the up and down arrows is underlined.

Modes:

Two modes were implemented in the program: mode 0 sets the application for the Training 1 (see section 4.5.1) and its test section before the rounds and the rounds including all rhythmic patterns used in this training; and mode 1 sets a different test before the rounds, a round management mechanic that alternates each day between the rounds of day 1 and day 2 of the evaluation trainings (trainings 2 and 3 mentioned in sections 4.5.2 and 4.5.3), as well as the texts of the right hand and left hand alternating each time that a round is saved. Despite the difficulties that I had managing the indexes of the rounds the modes because the proper testing of this functionality required that I save a round each time, the modes of the ARTA were relatively easy to program. To test the rounds mechanics, I had to speed up the tempo to the maximum and wait for the whole rounds to finished before saving them and confirm that it worked as expected.

Important performance related functionalities:

During a training session, different data can be saved in a performance folder. Here in Figure 19 is an overview of the performance folder's structure:

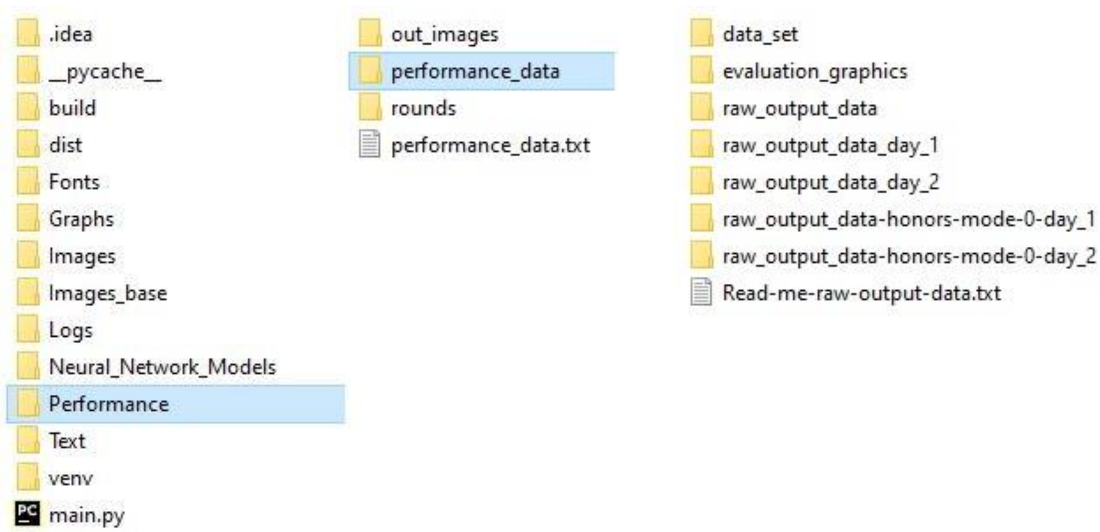


Figure 19: Structure of Performance folder the ARTA

1) After each test and part section, performance graphics are automatically saved in the evaluation graphics folder. In mode 0, they are saved in the same folder and in mode 1, in two different folders for performance files of day 1 and 2.

2) At the end of each round, a window called "Training Validation Window" appears, through which the round's raw output data (saved performance files) can be saved. To ensure that the data was valid, the participants (including myself) could check boxes if they had technical problems or were distracted during the training, which could have affected their performance. If that was the case the file of this round was simply not saved and had to be restarted entirely. In mode one, all files were saved in the folder raw_output_data and in mode 1. There were two folders: raw_output_data_day_1 and day 1 and raw_output_data_day_2 for the respective training days 1 and 2.

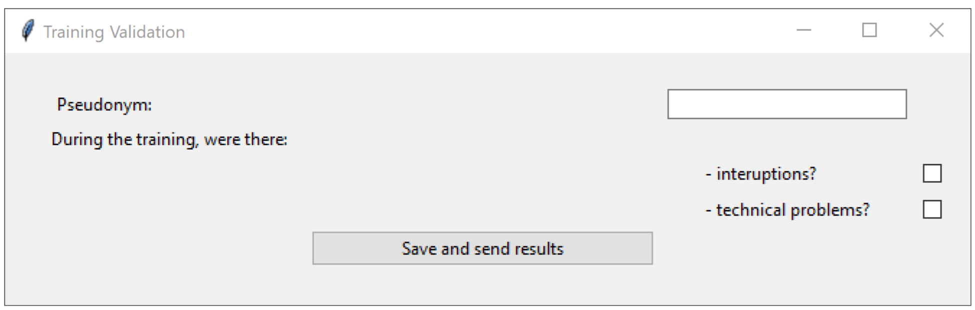


Figure 20: Training Validation window to manage the saving of performance files after each round.

3) After the training, it was possible to save the output matrix of the round, which had a shape of 600 x 28 (600= total runits in one round; 28= number of runit parameters for each runit).

4) From this data, the total number of input data for the ANN could be reshaped in "time windows" for the neural network is 384 per round and their shape is described in section 4.1.3. All the raw output data in the folders were reshaped in this way and combined together as NumPy arrays (vector and matrices data type in Python language) in two text files to be the complete dataset for the ANN: one for the X values of the dataset (input data) and one for the Y values (ground truth values – the answers that should be predicted

by the ANN). Those were the ANN's data set. It was then separated into training and validation sets in a ratio of 4/5: 80 % training data and 20 % for the test data.

The rhythmic patterns:

To have a good flexibility of implementation of different types of rhythms like 2/2, 3/3, 4/4, 5/5 and 6/6, all rhythmic patterns implemented in rounds consisted in 24 runits of equal time length and the definition and each Part section of a round had a total of 120 runits. 120 is a multiple of 1, 2, 3, 4, 5 and 6. A half-pattern constitute of the 12 first or last rhythmic values of a rhythmic pattern.

Runits (rhythmic units): A rhythmic unit is a class in the ARTA's program. This name was chosen because of the fact that they can, not only represent a note, but also a silence value and each one has a total of 28 attributes (parameters). Some properties of runits are relevant to the physical representation of their text characters on screen and their management in internal lists of the program, some are the values of the adaptive parameters at the moment when the runit should have been pressed and the rest are used for the rhythmic patterns, timing and performance. A description of the exact structure of the output matrix (which is saved as raw output data into the folders), can be found in section 4.3.1. All those parameters were then used to train the ANN. Important to understand, is that all values used by the output data matrix are between 0.0 and 1.0, because neural networks typically work with data with values between 0 and 1 or -0.5 and 0.5. Four types of rhythmic values constitute the rhythmic patterns:

1. **Silence** (no key is pressed) - value: 0.0
2. **Soft** (pressed softly) - value: 0.3
3. **Accent** (pressed harder – with a rhythmic accent) - value: 0.6
4. **Zoom-In** (attention zoomed in the finger tip) - value: 0.9

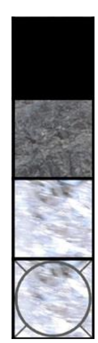


Figure 21: rhythmic values

The 3 first values in Figure 20 represent all the rhythmic values used in conventional RTM mentioned in section 2.2.1.2 (silence, note and accentuated note) and here is what they meant in the context of this project: Silence, no key was to be pressed at that time; Soft, key had to be pressed softly; and the Accent, key had to be pressed with accentuation (with slightly more pressure). Although the keyboard is not touch-sensitive, the participants were asked to make the pressure distinction for each movement. The 4th value, Zoom-in, is the same as the Accent value, except that the Zoom-in technique explained in section 2.3 is applied: the attention is of the participant is zoomed-into the sensation of the tip of the finger that is pressing the key. The reason for the Zoom-in values is to generate theta waves in the brain during the exercises to optimize the learning performance (see the whole section 2.4 for the scientific evidence that led to that element). Considering the resources available for the evaluation training parts of this project, it was impossible for me to verify whether or not the participants really made the pressure distinction or not, or if they could focus their attention appropriately for the Zoom-in values, but they understood the purposes of the project and agreed to follow those instructions.

I also communicated with them during their training to ask how they were doing and emphasized the importance of the pressure changes the attention in the finger tips.

Performance results graphics:

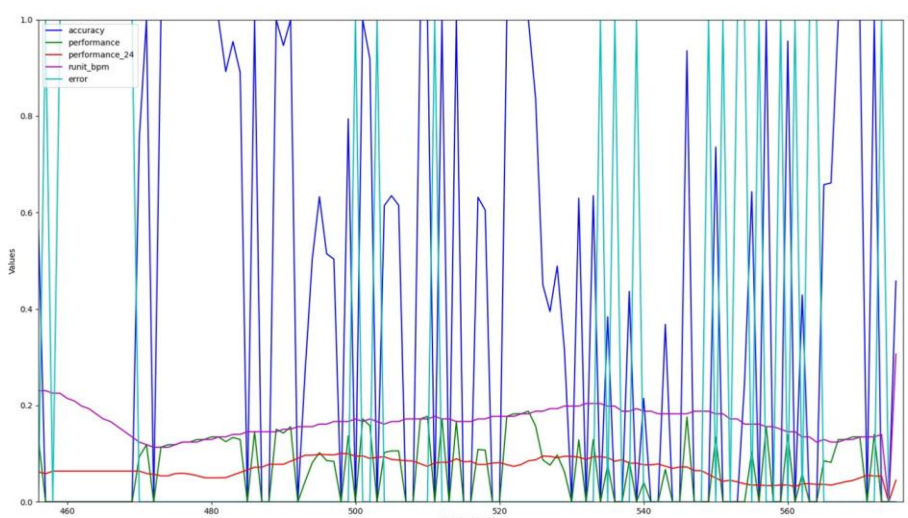


Figure 22: Saved graphic from the Part 4 section of Training 1

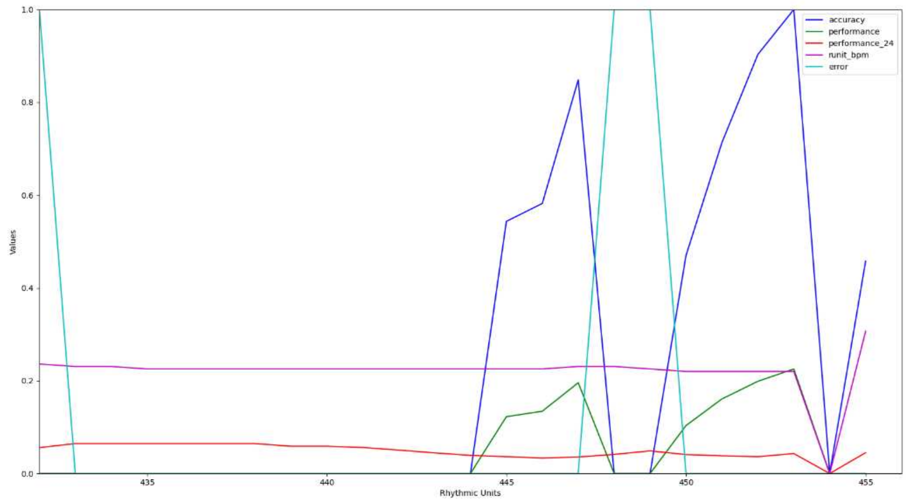


Figure 24: Saved graphic from the Test 4 section of Training 1

4.2 Adaptive mechanic

At the end of Training 1, I analysed the graphics and observed important tendencies.

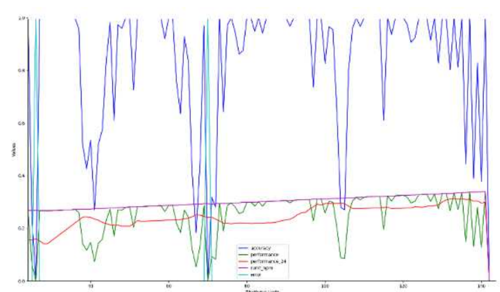
1. The order of the parts in the same round is important in predicting the performance of the next one, because it determines the starting speed of the next round;
2. The best performance was achieved in Part 1, which is not surprising, because there are no Silence values in the rhythmic patterns of this section, to the contrary of all the other rounds. Part 1 is efficient for building performance (speed and precision)
3. The best speeds were achieved in Part 2: this is at least, partly due to the speed reached in part 1, but also to the fact that in Part 3, the speed started to be too fast for me and I made more mistakes that slowed the speed down. Part for had only random rhythmic patterns and it was harder in general to build speed in that section.
4. The sequences full of notes (Soft, Accent or Zoom-in values) alternated by Silence values (one or more) as in part 2 are efficient at building speed;
5. The adaptive mechanic parameters associated with the best performance had a tempo progression ratio of 0.52 (**t_mofication_freq** = 2.5; **t_modification_step =** 1.3)

In Table 1, adaptive parameter values were taken from Part 1 and Test 2 sections, where the best performances were achieved in the first training. The calculated average tempo progression function of the values was Y= 0.52X.

(t_mofication_freq, t_modification_step)
Part 1 section
(2,1) (4,1) (1,1) (1,1) (3,2) (2,2)
Test 2 section
(2,1) (5,2) (2,1) (2.1)
Average values of Part 1 and Test 2 combined
(2.5, 1.3)

Table 1: Calculation of the adaptive parameter values (tempo progression curve)

I implemented 4, for t_mofication_freq (4 notes successfully pressed without error) and 2 for t_modification_step (number of BPM to append each time). I observed during my training, that although I reached the best performances with smaller t_mofication_freq values, that the fingers would get tired very fast and it felt more natural when this value was higher. In the second evaluation training, I modified the values **t_mofication_freq** and **t_modification_step** for 2 and 1, respectively, keeping the same tempo progression function, but allowing the speed to increase faster after errors were made.



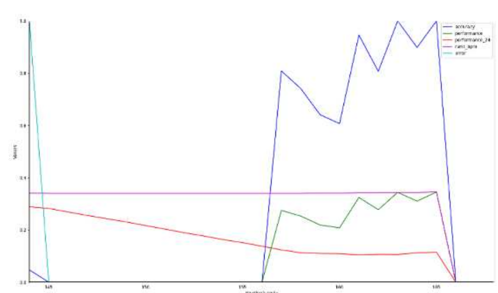


Figure 25: Figure 26: Examples of one of the best performances achieved in the sections Part 1 and Test 2

4.3 Research about AI – Deep learning techniques

4.3.1 Data types, shapes and disposition

In the planning of this project, I had a conversation with Kiedrowski, who produces Youtube tutorial videos about machine learning in Python under the name of Kie Codes. I explained the methodology that I had in mind to teach a neural network to predict human performance on rhythmic training tasks. He kindly offered his time and he thought that the parameters I had in mind and the methodology made sense. He gave me the tip to upload the performance data on a database, MongoDB. Having read a lot on the subject and watched many tutorials, I started to experiment with a CNN network, which code for image recognition tasks that was given in a tutorial on Youtube. I implemented a method to display the data as images, because I though it would be easier to start machine learning with a visual approach. This is how the files of the time windows shaped data explained in section … looked like in the folder (Figure 27):

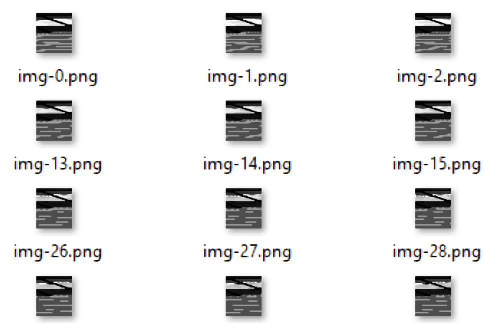


Figure 27: Time windows shaped data (X data set) implemented as images

This was very good practice to manipulate shapes and multi-dimensional matrices (NumPy arrays). I discovered later that Python's matplotlib package has an already implemented method that does exactly that, so I used it instead of mine to display the results of all the ANN's predictions for the rest of the project. Here is the first shape I used:

Input Data for the Convolution Neural Network

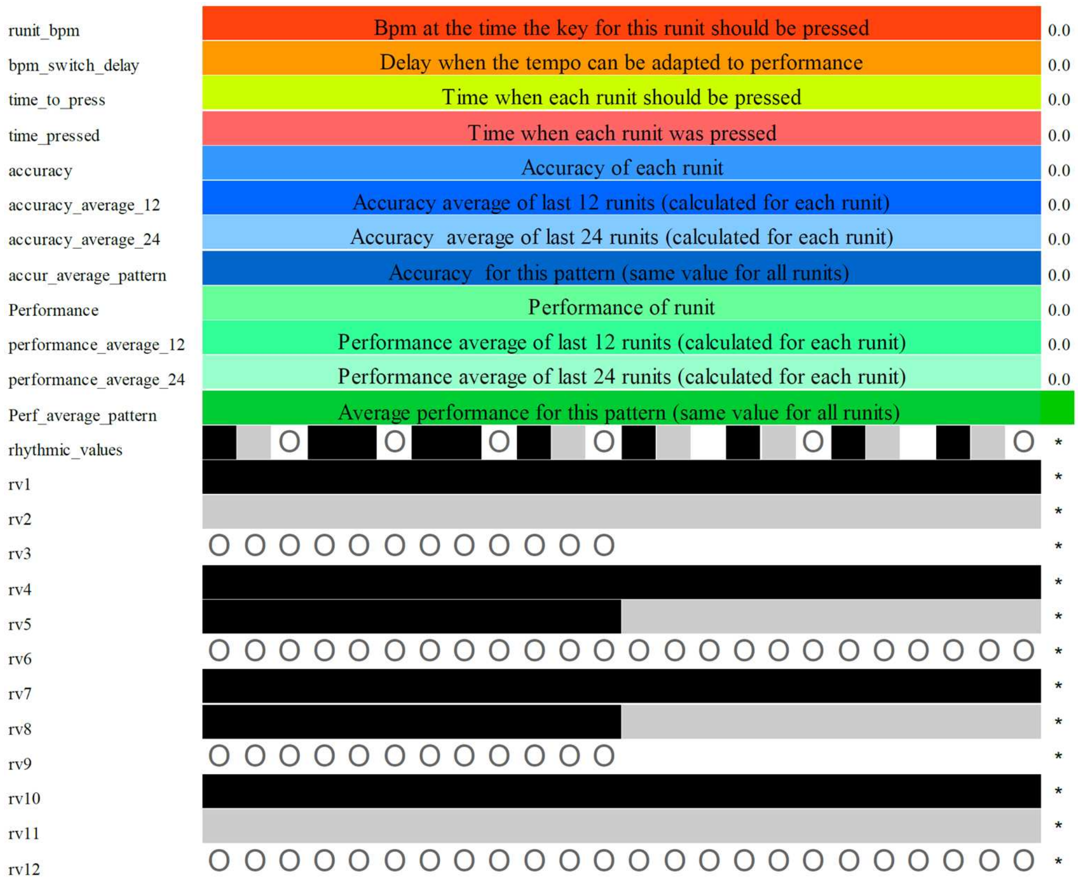


Figure 28: 1st time window X data shape used for the CNN

Input data X: (1 x 25 x 25 x 3) - NumPy array shape (1 ,25, 25, 3)

Output data Y: (1 x 25 x 3) - NumPy array shape (1 ,25, 3)

Description: The parameter ***Perf_average_pattern*** is the average performance obtained for the present rhythmic pattern (which has 24 values). The last value on the right end (in green) corresponds to the performance average of the next rhythmic pattern. The asterisks correspond to the rhythmic values of the first half of the next rhythmic pattern. The neural network is trained to predict those 12 values. All other values were set to 0. The Y data corresponded to the last column of the X data before its values were replaced by the asterisks and 0 values.

Structure of the dataset for the LSTM and bilateral LSMT

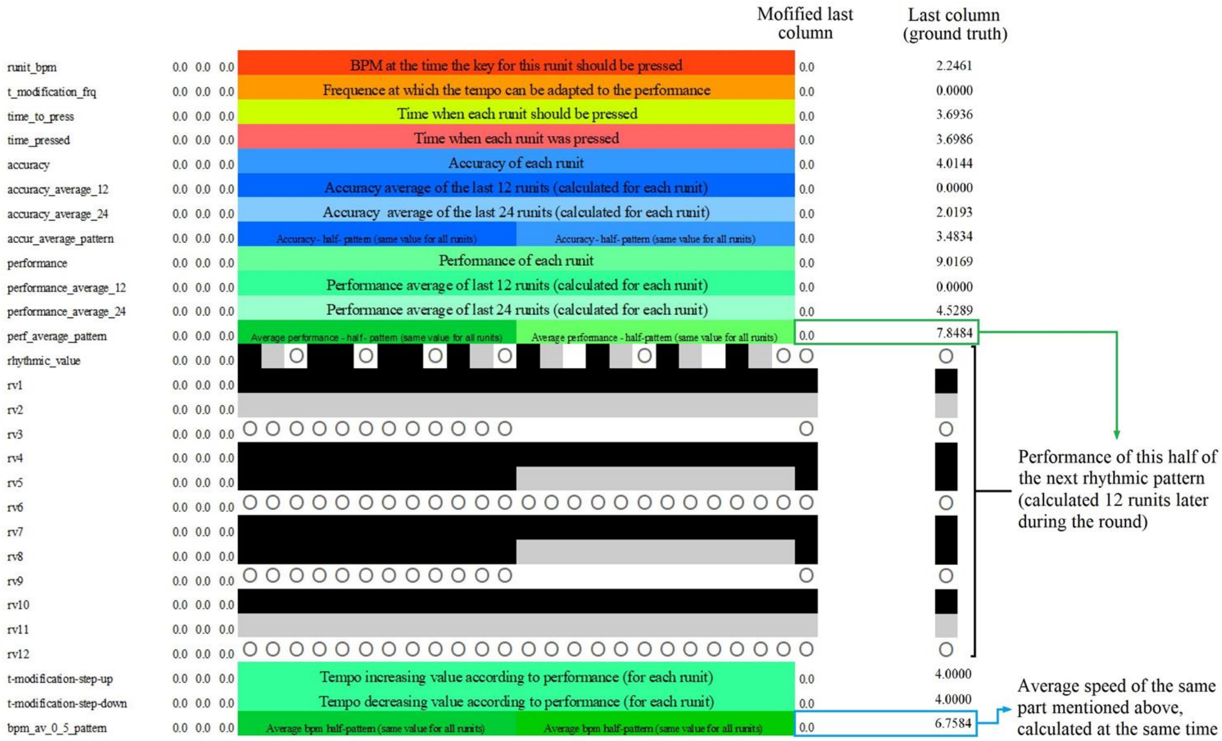


*Figure 29: 2nd time window data shape X and vector data shape Y used for the LSTM and BLSTM - **Left:** Input data (X): 1 x 28 x 28 – NumPy array shape = (1 ,28, 28)*

***Right:** Ground truth data (Y): 1 x 28 - NumPy array shape = (1 ,28)*

Description: The parameter ***Perf_average_pattern*** is the average performance obtained for the present half rhythmic patterns (which both have 12 values). The last value (the three points) on the right corresponds to the value of the next first half of the rhythmic pattern. The three points at the end of the three last parameters correspond to the t_modification_step of the adaptive mechanics values and the speed average of the first half of the next rhythmic pattern. The neural network is trained to predict all the values of the last column. All the values of this last column before they were replaced by the 0 values and asterisks constitute the output data (Y data). Although the prediction of all those values are taking resources of the neural network, It was relevant for me to see exactly how they were predicted, especially of the values of **rv1** to **rv12**, to see visually how accurate the predictions are, but also to notice intensity variations in them. The most important value to be predicted was of course, the average performance of the next half-pattern: ***Perf_average_pattern***.

Output Matrix from the ARTA

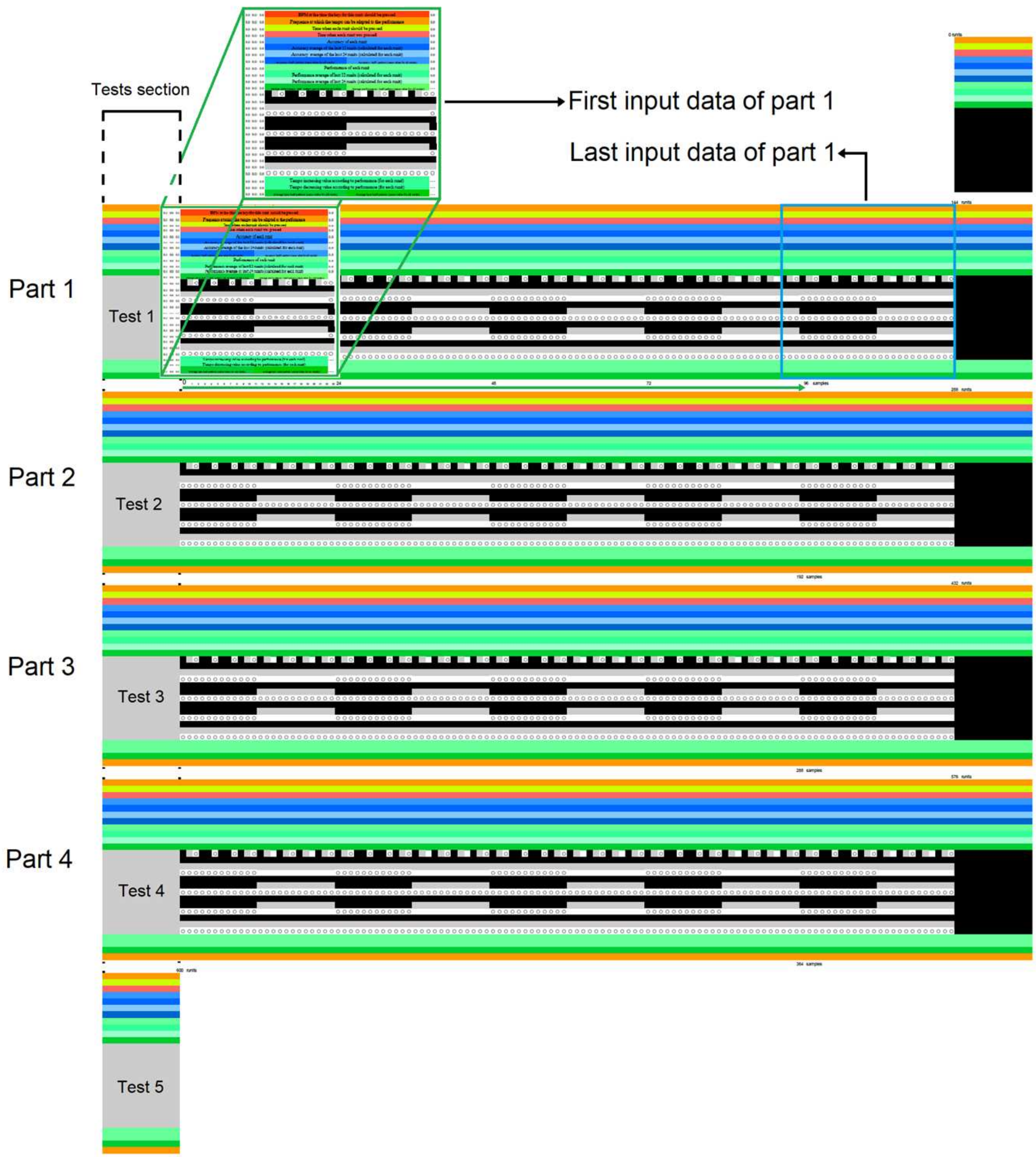


Figure 30: Structure of the ***raw_output_data*** *performance files: 600 x 28 - NumPy array shape = (600 ,28)*

The raw output data performance file is the performance history of the saved round, where all the parameters seen in Figure 29 are appended each time a runit should be pressed. The data was than reshaped into the time window data shapes described in figures 28 and 29. A total of 384 X and Y input data for the final data set of the ANN was generated for each round.

4.3.2 Choice of parameters

For each of the 600 runits per round, 28 parameters were appended to the output matrix. They are listed in Table 2 with their respective indexes in axis 1 of the matrix. For the performance optimisation process used to generate new RTM, only the values of section two were implemented in arrays and displayed as images.

Index	Parameter	Index	Parameter
Section 1		Section 2	
0	runit_bpm	11	perf_av_0_5_pattern
1	t_modification_frq	12	rhythmic_value
2	time_to_press	13	rv1
3	time_pressed	14	rv2
4	accuracy	15	rv3
5	accuracy_average_12	16	rv4
6	accuracy_average_24	17	rv5
7	acc_av_0_5_pattern	18	rv6
8	performance	19	rv7
9	performance_average_12	20	rv8
10	performance_average_24	21	rv9
		22	rv10
		23	rv11
		24	rv12
		25	t_mod_step_up
		26	t_mod_step_down
		27	bpm_av_0_5_pattern

Table 2: List of all 28 parameters of each runit with their respective indexes. The parameters in section 2 are represented in the images of the predictions results of the ANN.

4.3.3 Convolution Neural Network

At first, I found it easier to get into the subject of deep learning by focusing on image recognition, which allows a very visual and simple way to represent the data. The input images are converted into arrays and the outputs can be shaped for one's purposes. Because of the shape of the ARTA's output matrix data described in section 3.1.3 it was reasonable for my skills at the beginning to reshape it exactly into the 4-dimensional shape of the convolution neural network that I had at hand (1, 25, 25, 3). The output data was shaped as a vector and represented as an image of 25 x 1 pixels.

After having generated approximately 10 000 data and experimented with this first neural network, I obtained for the first time an accuracy value for the validation set over the random value of 50 %, but the results remained fairly low.

```
Epoch 60/64
60/60 [==============================] - 9s 152ms/step - loss: 0.0446 - accuracy: 0.3880 - val_loss: 0.0422 - val_accuracy: 0.6516
Epoch 61/64
60/60 [==============================] - 9s 150ms/step - loss: 0.0446 - accuracy: 0.4125 - val_loss: 0.0421 - val_accuracy: 0.4547
Epoch 62/64
60/60 [==============================] - 9s 146ms/step - loss: 0.0446 - accuracy: 0.4042 - val_loss: 0.0422 - val_accuracy: 0.5078
Epoch 63/64
60/60 [==============================] - 9s 145ms/step - loss: 0.0446 - accuracy: 0.4354 - val_loss: 0.0422 - val_accuracy: 0.6594
Epoch 64/64
60/60 [==============================] - 9s 150ms/step - loss: 0.0446 - accuracy: 0.3781 - val_loss: 0.0422 - val_accuracy: 0.6438
16/16 [==============================] - 0s 15ms/step - loss: 0.0490 - accuracy: 0.5859
```

Figure 31: First results over 0.50 with the convolution neural network

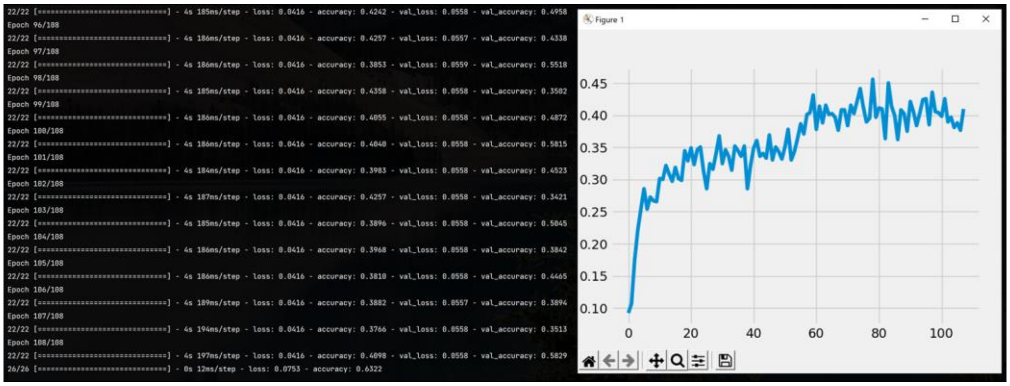


Figure 32: Second day with 4996 inputs

4.3.4 LTST and bilateral LSTM neural network

When I noticed that the results were weaker than I expected (at hoped for at least 70 % accuracy), I had the idea to change the shape of the input data, and train the neural network to predict, not a whole rhythmic pattern of runits (12 unknown values), given a single average performance value, but the other way round: the average performance and bpm values, the adaptive mechanic values (4 unknown values) given the whole rhythmic pattern of 12 known values). See the difference of shapes 1 and 2 (see images Input Data for the ANN and Input data for the LSTM and bilateral LSMT)

Although I obtained results that were a lot better, between 70 and 92% accuracy, the neural network was still not giving results that were concretely good enough to predict the performance of the next rhythmic pattern, which was purpose of the ANN. I researched more about techniques to predict human performance and was pleased to find someone who did something very similar to what I was trying to achieve, with a similar way to shape the data as time windows, and for a very similar application: predicting his performance at a rhythm game called OSU. He achieve good results with a LSTM neural network. I started to research on that subject and finally found a tutorial of Sendex where the author used and explained his LSTM with a data shape that was similar to the one I used. I reshaped my data again to make it fit to this network and the final shape was (1, 28, 28). Reading about hyperparameters and training techniques, I finally got some very good results for my purpose and later discovered a variation of LSTM, the bilateral LSTM, that I implemented and got the best results with after the 10 days training:

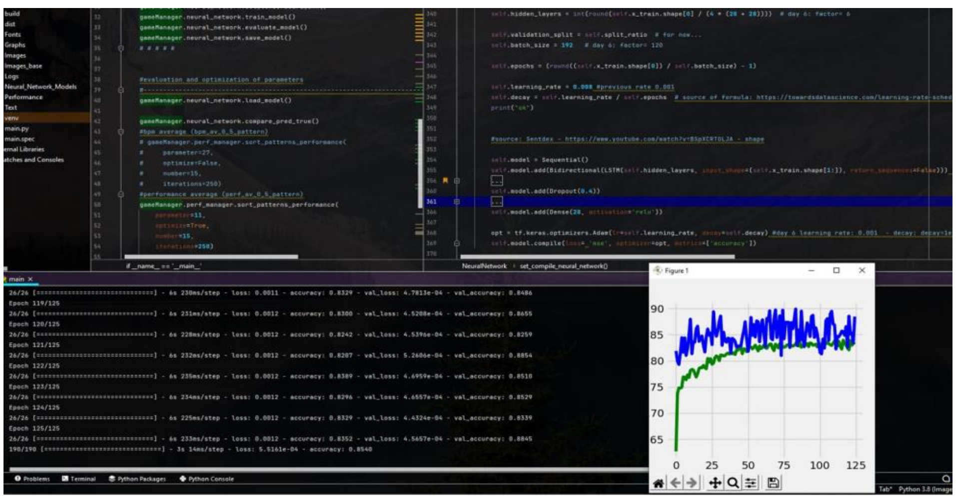


Figure 33: cross validation results 1

4.3.5 Performance optimisation process

After the BLSTM neural network was properly training, I sorted the rhythmic patterns of Training 1 associated with the best average performance and modified their X data, replacing only the rhythmic values of the last column, which correspond to the next half-pattern. I used the neural network to predict the average performance of randomly generated half-patterns (12 values). This process was iterated 250 times and each time, only if the predicted performance was better then the one of the previous iteration, the half-pattern and its prediction was kept, along with the initial X and Y data that was used, which is the context in the round, where that half-pattern would have led to a better average performance (according to the ANN's predictions). Figure 34 depicts the organisation and visual representation of the results of this performance optimization process to generate new half-patterns:

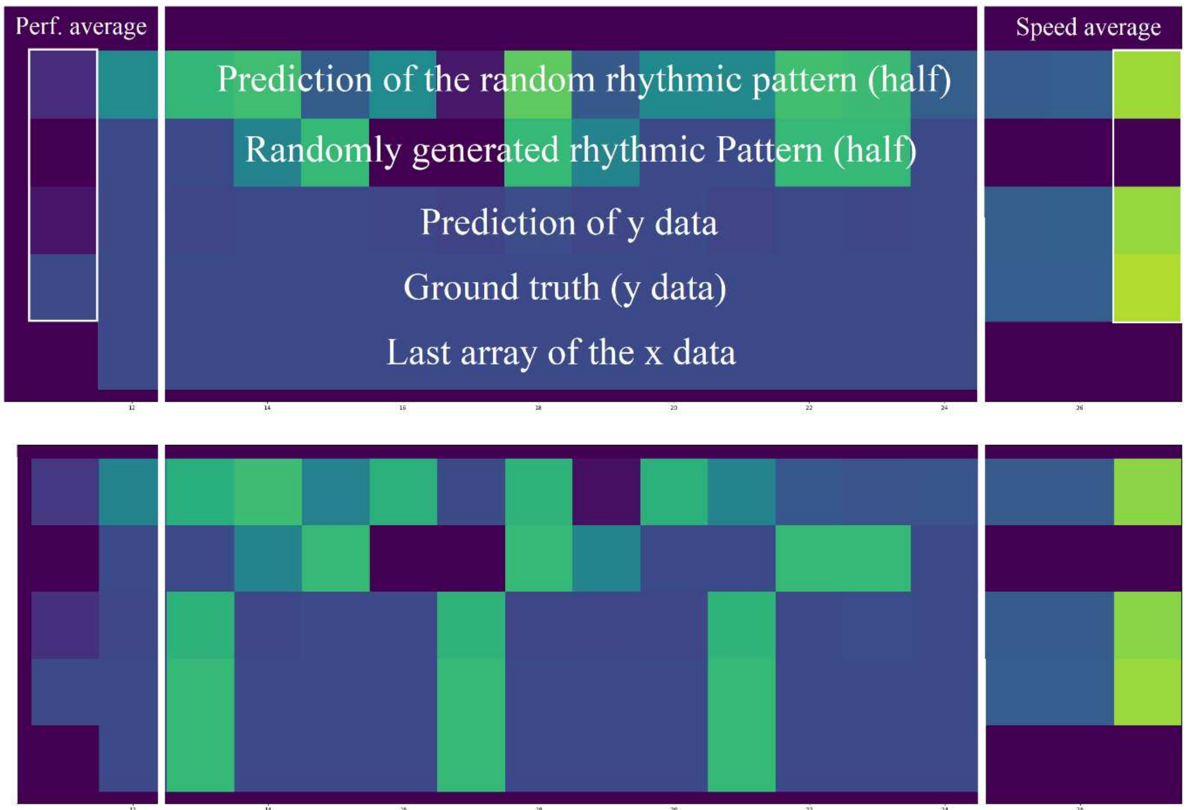


Figure 34: Performance optimization process using the BLSTM – Structure of the results

Here, the intensity of the colors depicts the value of the parameters 11 to 27, with the value 0.0 being the darkest color and 1.0, the lightest. The rhythmic values of the half-patterns can be seen between the white lines. As a reminder and for more clarity, the values are: 0.0 (Silence), 0.3 (Soft), 0.6 (Accent), 0,9 (Zoom-in). If one analyses closer, the values of the predictions can also be between the previously mentioned rhythmic values. There is here room for interpretation of what that might mean when practicing such a rhythmic pattern, but it suggests a variety of intensity of rhythmic accents, of finger pressure and as the intensity reaches nearer to the Zoom-in value, it suggests a variation of the intensity of the the attentional “zoom”into the sensation of the tips of the fingers. Despite this interesting possibility, I just chose the randomly generated half-pattern values to implement as new RTM and only focused on the fact that they are associated with a better average performance, according to predictions of the ANN.

4.4 Research about human learning performance

The results of this research are found in section 2.4.

4.5 Evaluation of performance and RTM with the ARTA

4.5.1 1st Training

4.5.1.1 Conception of the 1st Training

Day 1 and day 2 round structures:

The following image is a series of combined screen shots of the training of day 2. Each square is a runit and has a rhythmic value as explained here above. Each round consists in 5 test sections and 4 parts with different rhythmic patterns. The test sections have a pause of 12 runits, followed by 12 softs, they act as control points where the performance can be monitored without rhythmic variations. Part 1 and 2 are the earlier mentioned rhythm practice techniques described by Wallick and Wright, they are proven to be efficient ways of training. The next two parts are designed to feed the neural network with, so that it can be exposed to a variety of rhythms. I had a conversation with a good friend who is specialist in acoustic physics and has a bright knowledge in the field of music about rhythmic patterns and he suggested that the rhythms of Mozart might be very interesting, because of Mozart's well known genius abilities to perceive music as a whole. He suggested that I observe the rhythms Mozart's *Symphony No. 41 in C, K. 551.* I did so and implemented rhythms that I found interesting after practicing motor sequences with them to observe their effects on performance (doing jogging, practicing guitare chord transitions and signing exercises). The upper notes of the bass line at the bottom of the following part of this symphony is an example of rhythmic passage that was implemented in the first and second lines of part 3 of the rounds:

Figure 35: Mozart Symphony No. 41 in C Major "Jupiter", K. 551 – (musopen.org, 2022, p.10)

Finally, Part 4 has only randomly generated rhythmic patterns, to feed the ANN with very different patterns.

Overview of the rounds

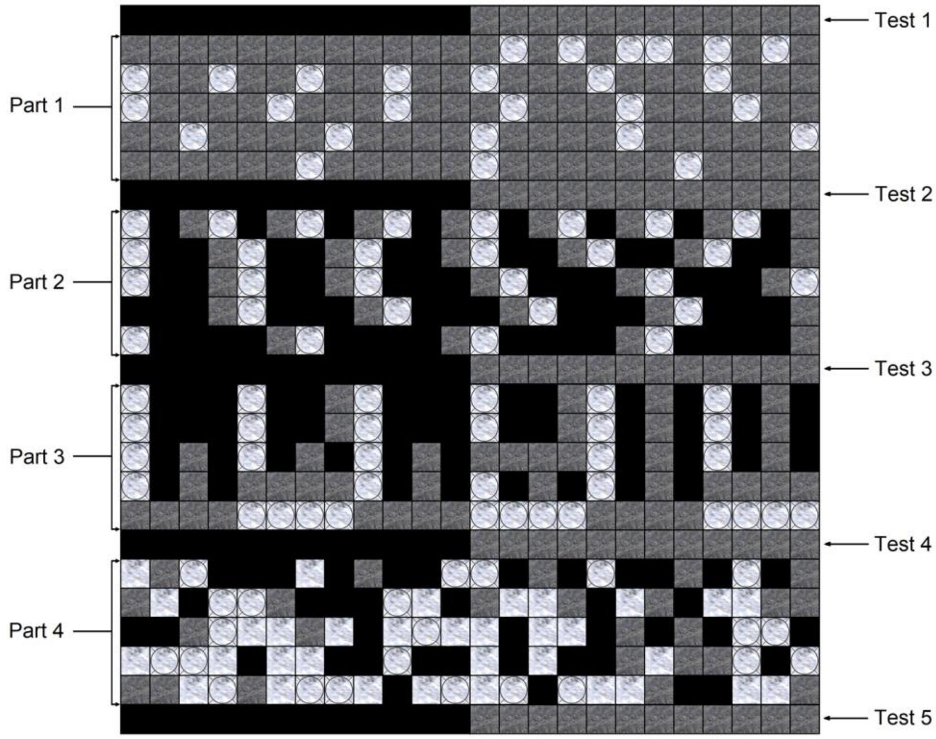


Figure 36: 1st training - All parts of a training round of day 2

Day 1 has the same structure as day 2, except that all the Zoom-in rhythmic values were replaced for Accents values, except for the random patterns of part 4 that had all 4 values.

4.5.1.2 Execution of the 1st Training

Initially, I had planned to do the fists training and focus only on adjusting the adaptive mechanic parameters in real-time.

4.5.1.3 Analysis of results – 1st conception of RTM

Results of the first 10 days training – (1 person):

For this training, a total of 30336 input data was generated out of the 79 rounds that were completed. For the neural network, the data was split into 24 269 training data and 6067 test data. Out of this data set, the 100 rhythmic patterns that were associated with the best performance and speed averages were organized and displayed in NumPy arrays and displayed as images, to allow to see the results as a whole, with all patterns seen at once:

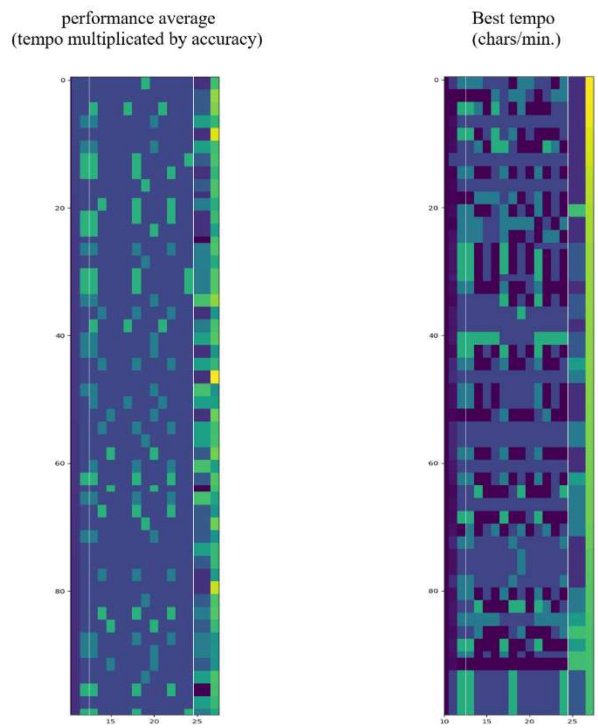


Figure 37: Training 1 – Rhythmic patterns associated with the best performance and best bpm values

In the above images, each row has a rhythmic pattern, they are listed in order from top to bottom, the best ones being on top and as the lower rows have inferior values. In each row, the rhythmic patterns are between the white lines (indexes 13 to 24 inclusively). The average performance values are on the left side (index11) and the average bpm on the right (index 27).

I selected the 25 best patterns for performance average on the left side of Figure 37 and executed the performance optimization process explained in section 4.3.5 with them. Instead of always using the same trained neural network model, I did some cross validation, as advised by my friend Rohit, software engineer: the ANN was trained 10 times differently, with the same hyperparameters, but order of the input data was shuffled each time, to assure that the predicted patterns are not similar or identical by "luck".

He gave me this advice after I had told him that the results showed identical patterns repeating several times, as seen in Figure 38, which is one of the two images that I documented.

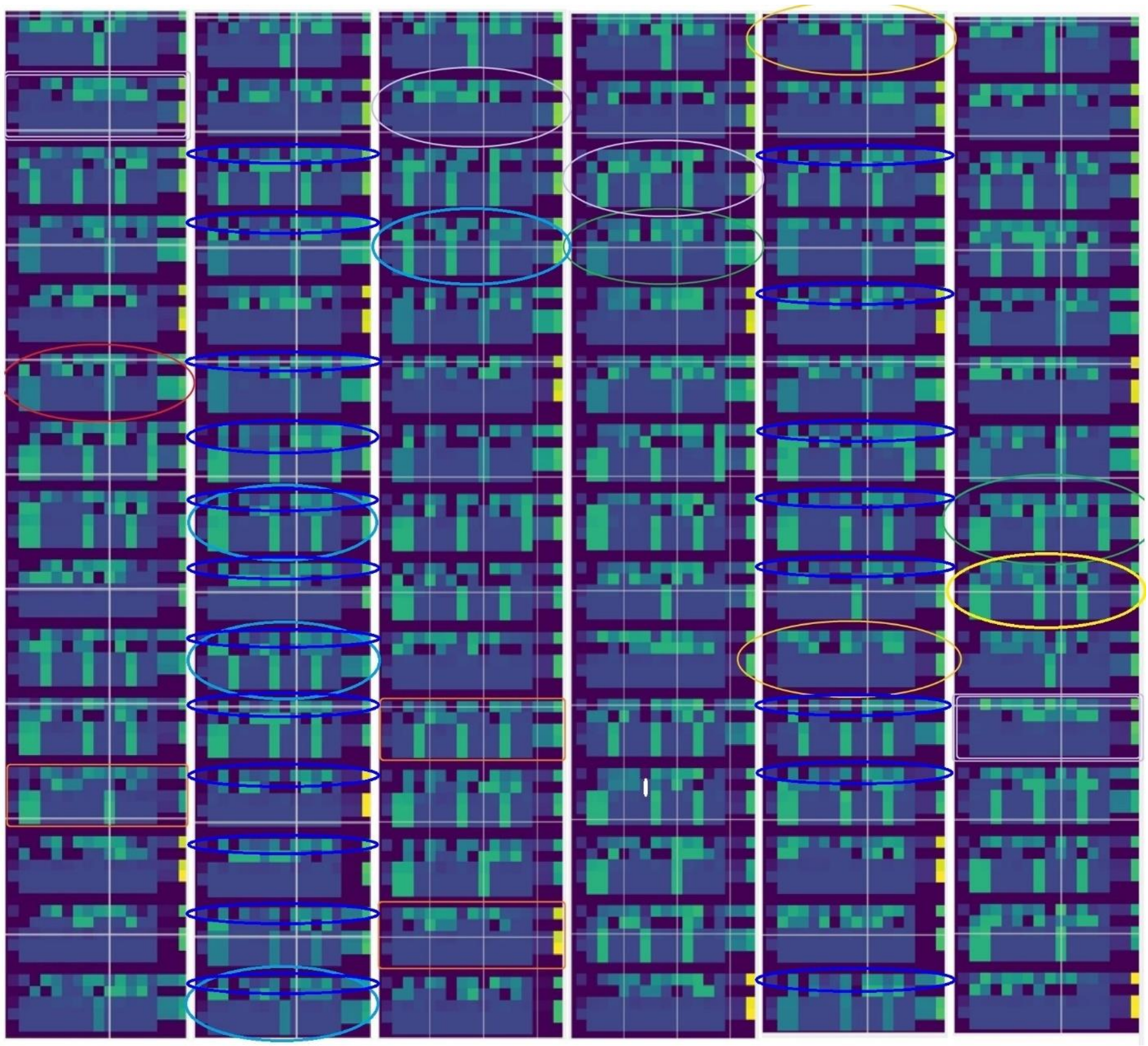


Figure 38: Optimized rhythmic patterns with identical patterns (invalid batch)

I discovered that this was due to a subtle syntax error in the code and I had to start the process over again after correcting it. Those are the results that I used to generate the new RTM:

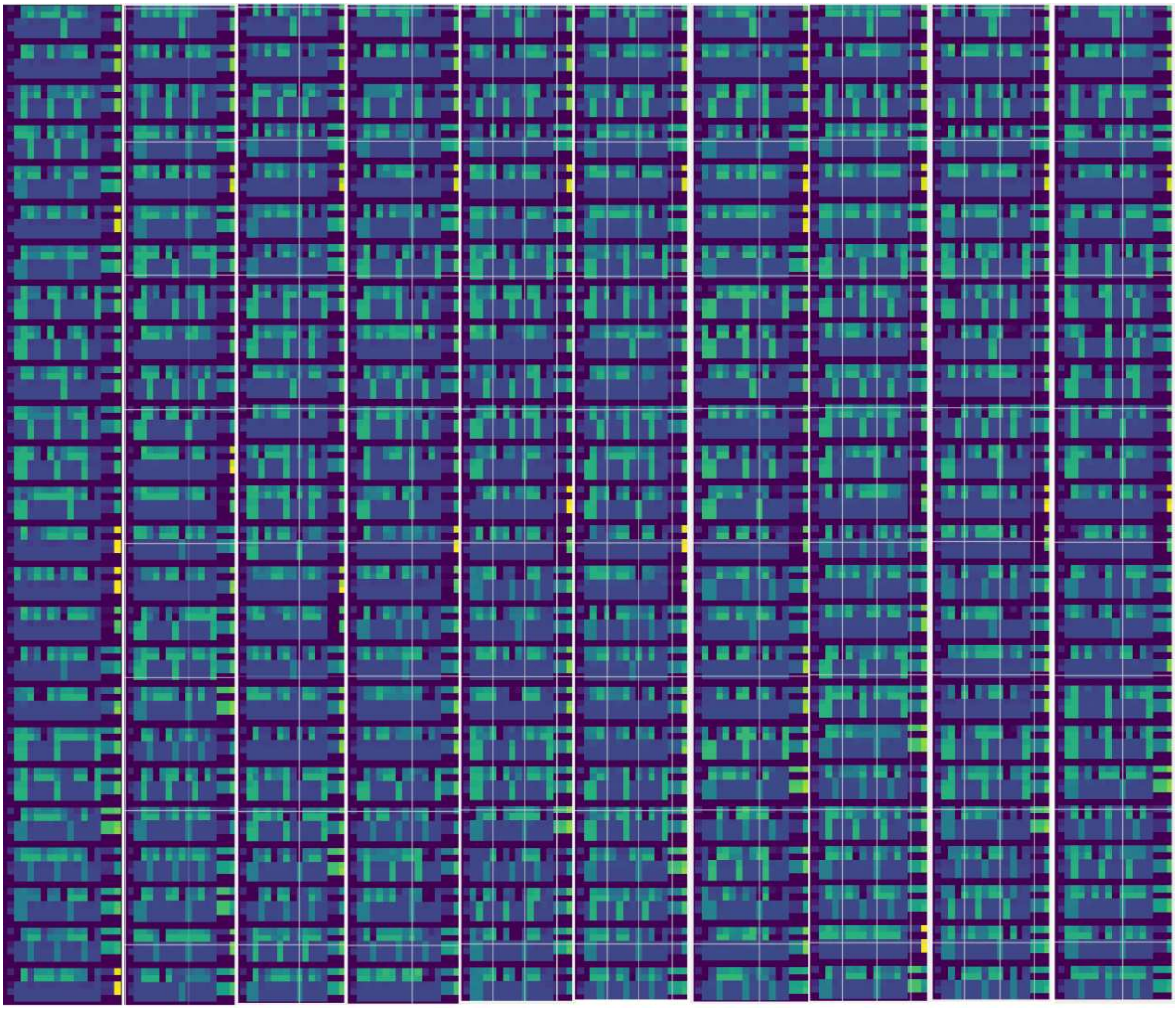


Figure 39: Results of the performance optimisation process

Among the 250 patterns, I selected some with features and structures that repeated often, taping the rhythms on my laps to see if they made sense, if they felt efficient enough to choose them. The patterns that I sorted out are not only the result of this optimization process, but also of my personal experience practicing with them and this is part of the self-monitoring of this project. The formal evaluation of their efficiency took place in Trainings 1 and 2. In theory, I could have chosen all of the 250 patterns, but I restrained my choice to patterns of the 3 families that I clearly identified as having common features and a similar structure. Here is what those families looked like:

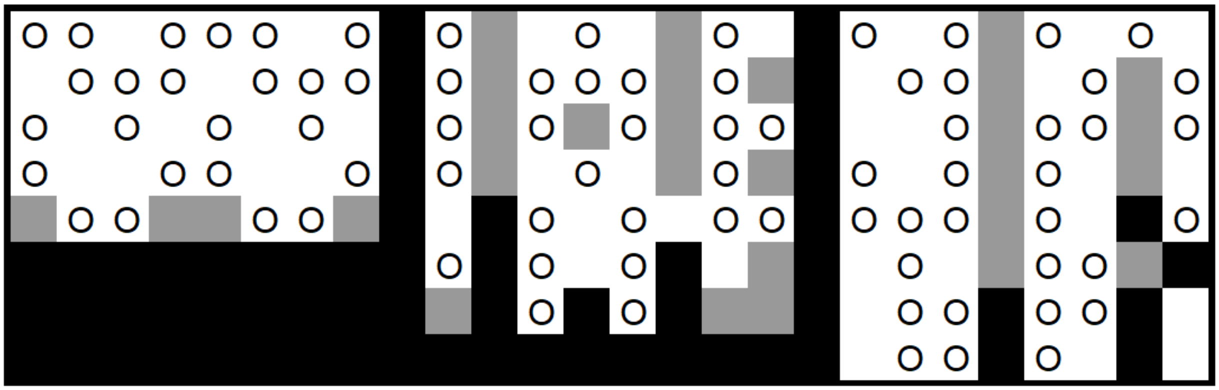


Figure 40: Three families of rhythmic patterns sorted out of the results in Figure 39

4.5.2 2nd Training (1st evaluation training)

4.5.2.1 Conception of the 2nd Training

For this training, four people were found, 3 men and 1 woman. They accepted to do 10 days of training, over 2 weeks, with never more than one day of pause between the trials. Each day, 4 rounds were to be executed. The trainings alternated from day 1 (conventional RTM) and day 2 (new optimized RTM), for a total of 5 days of each training sessions alternating each day (day 1, day 2, day1, day 2...)

Rounds:

The rounds were structured the same way as for my first training, except that the first 24 runits were replaced by a whole row of silences. This was necessary to implement the round dynamics that changed the text from the left hand (**fsda**) to the right hand (**jlk;**) and to change this text only if the round was saved. The saving happens at the begining of the next round, to allow the parameters of the last runit of each round to be calculated, because they can be pressed before or after the right time (**maximum pressing delay**= 1/2 note's time value - before or after the note (runit)) without error. Each completed round, the order of the letters (left or right hand's text) would be changed to allow a rotation of the letters, so that the all can be equally accentuated with the different rhythmic values of rhythmic patterns after 4 rounds of the same hand.

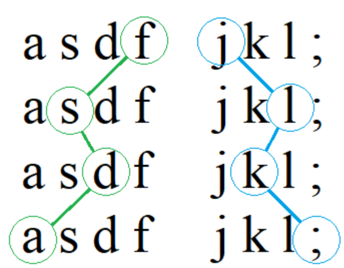
Text patterns:

The reason why those two particular text patterns have been chosen are the following:

1. Unlike in the first training, where the goal was to have the simplest pattern possible allowing a transition between letters (2 letters) to be practice with rhythmic patterns. This training aimed at evaluating any the learning performance for longer patterns, but to keep it as simple as possible and prevent finger injuries from always training the same two fingers for 2 weeks, I chose to share the weight to 4 fingers of each hand.

   All rhythmic patterns of the new optimized patterns have 8 runits. To allow a good rotation of the indexes withing the text (in programming languagesm index refer to the order of the elements in a list, array character chain, etc.), the text had to be as short as possible. 4 letters per hand made much sense, since it is a multiple of 8. The left hand's text characters indexes were incremented by 1 after each round as follows, and the right hand's text also had the same logic implemented: **fsda - afsd - dafs – dafs - sdaf - fsda – etc.**

2. These texts allow to alternate the training between left and right hands, which is also well known strategy mentioned by pianists in Wallick's study (Wallick, 2013, p.91-101) To avoid that the execution would be to easy and the tempo to augment too fast for the performance of the ARTA, which had a maximum of 750 bpm (for computers with good RAM memory), with only whole notes time values, the letter order was rearranged in such way that the direction changed always from left to right or the other way round and the patterns of both hands are symmetrical. The movement can be seen in image (...)



Left and right hand patterns: fsda and jlk; - respectively

3. Those letters constitute the root positions for both hands in the 10 fingers typewriting system and aside from the evaluation purposes of this project, the participants could practice a meaningful hand posture for typewriting to work on computers.

   Rhythmic patterns: Figure 41 contains the round structures that were planned for day 1 with new RTM and day 2 with conventional ones for Training 1:

Rounds of Training 2

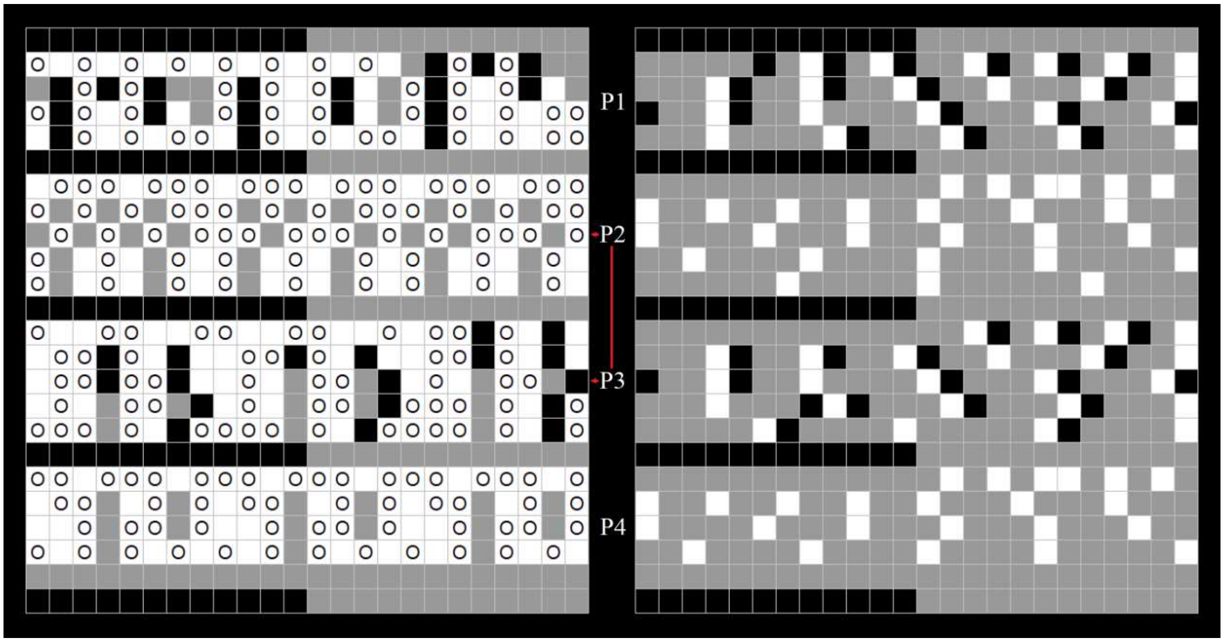


Figure 41: Rounds of day 1 (optimized RTM) and day 2 (conventional RTM) of Training 2

4.5.2.2 Execution of the 2nd Training

After two days into the training, I realized that the starting speed calculated at the beginning of rounds could vary significantly from one round to the other and from day to day. This would have made the comparison of the rounds of day 1 and 2 very hard, especially for the first sections. I contacted all participants and asked them to type the characters at the beginning of each round at approximately the same speed for day 1 and 2 and that this speed could increase from day to day but stay approximately the same for both trainings days. Later on in the training, I also realized that I made a huge mistake: I inverted the parts 2 and 3 of day1 when I implemented them. It was though that the amount of Silence values would be comparable for each section of both training days, because although no mistake is made if no key was pressed on a Silence value, the speed only appends when characters are successfully pressed and the performance value is a multiplication of the accuracy and speed. Important to know is that I reduced Silences for the conventional method to the very minimum time length (1 Silence between the notes) but as presented by Wright (section 2.2.1.2 – point 2) the pause between the notes is normally longer. The efficiency in terms of achieving the best performance in the shortest time possible would in fact be lower, at least in the context of the rounds of this training.

A second advantage of the conventional methods in this training is that Part 1 and 2 of the conventional methods are repeated almost exactly the same in Parts 3 and 4. As a result, despite that the practice time for day 1 and 2 were comparable, four round were to be done each day, conventional RTM were executed 2 times more than the new ones. A third advantage that I gave The conventional RTM is that the optimized method started first. Because of the structure of the evaluation that involves only one group of participants, it is impossible to measure the cross-learning effects that happens from day to day, how the training one day 1 affects the training of day 2 over time and vice versa. The only valid measurement that could be done record how the performance evolved within the rounds themselves.

It is also important to mention that I had problems with the saving of the performance data. In the implementation of the Training Validation window, I made a mistake that had some impact on the results. When the saving button was clicked twice to save the same round, everything se3emed to work well, but I noticed that the saved files had another size: instead of 411 bytes, they had 406 or 413. It is only when I implemented the training evaluation functionalities with the graphics, that I noticed that the structure of the matrix in these files was altered and unusable. Fortunately, there were just a few of them. I worked on correcting this mistake. Also, participants had told me that they sometimes did one round more or less in the same day and I had to find a solution for these two problems affecting the results.

It is important to explain clearly how I solved this problem. In the 10 days of training, the first and second days were compared together, also the third and fourth and so on. They were grouped in this way in pairs. For each pair, if a data file was unusable or missing, the associated round of the other day was erased. For each pair, I verified that the data also compared chronologically. For example, if the last file of one day was removed, the last one of the others was also removed. The total of data files of the training equal for day 1 and 2.

4.5.2.3 Analysis of results

A total of 152 usable performance files (76 rounds for day 1 and day 2) was generated by the four participants. 58 368 reshaped input data were generated: 46694 for the training set and

11674 for the validation (test) set. Out of the 4 participants, one obtained results that were significantly lower than the 3 others for day 1 (new RTM). For this reason, I generated results for 3 and 3 participants. Figure 42 shows the Average performance for the 8 last days of this training.

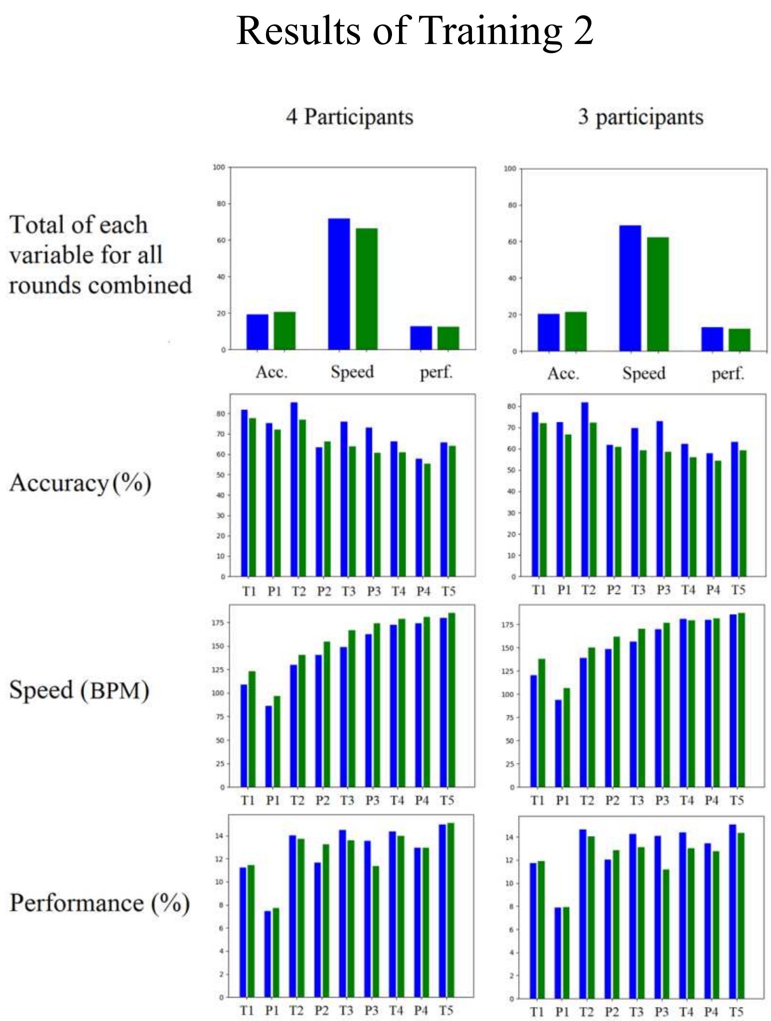


Figure 42: Results of Training 2 - Average performance for the 8 last days of the training for each round sections and for the cumulated training. In blue: day 1 (new RTM) – In green: day 2 (conventional RTM)

For each round sections of day 1 and 2, the performance parameters were compared, as well as the total of the accumulated performance averages of all rounds of the training. It could be attributed to the difference in speed at the beginning of each round during this training, but the results show that the performance and accuracy was better for day 1 from Test 3, Part 3, Test 4, Part 4 and Test 5 sections.

Best rhythmic patterns:

Figure 42 shows the rhythmic patterns associated with the best performance and speed averages for the whole training including all participants. The patterns with the lighter colors are all new rhythmic patterns including the Zoom-in values in yellow (left side) and green (right side). I do not know precisely why the colors are not the same for both images, but the different rhythmic values can still be identified on the right, although the general intensity of colors is lower.

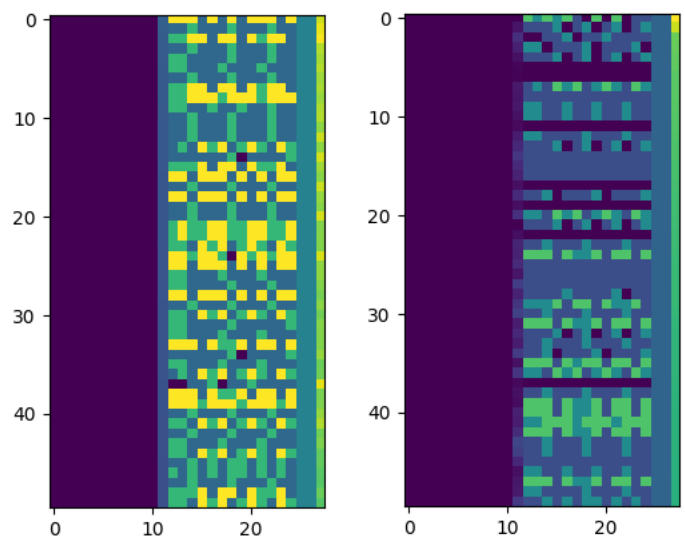


Figure 43: Rhythmic patterns associated with the best performance

Average (on the left) and speed average (on the right) during Training 2

4.5.3 3rd Training (2nd evaluation training)

4.5.3.1 Conception of the 3rd Training

This training was not initially planned but because of the errors made in the execution of Training 2 mentioned in section 4.5.2.2 (the unusable files and the inversion of Part 2 and 3), I decided to organize this training where I corrected the issues and having seen results of the previous training, I reorganized the rounds of day 1 and 2, so that the number of silences would be exactly the same in Part 1 and 3. I set the starting speed to a constant value of 80 bpm for each round, to be able to measure more precisely the differences in performance of the first sections of day 1 to day 2 and to avoid losing training efficiency when the starting tempo was too high.

Rounds of Training 3

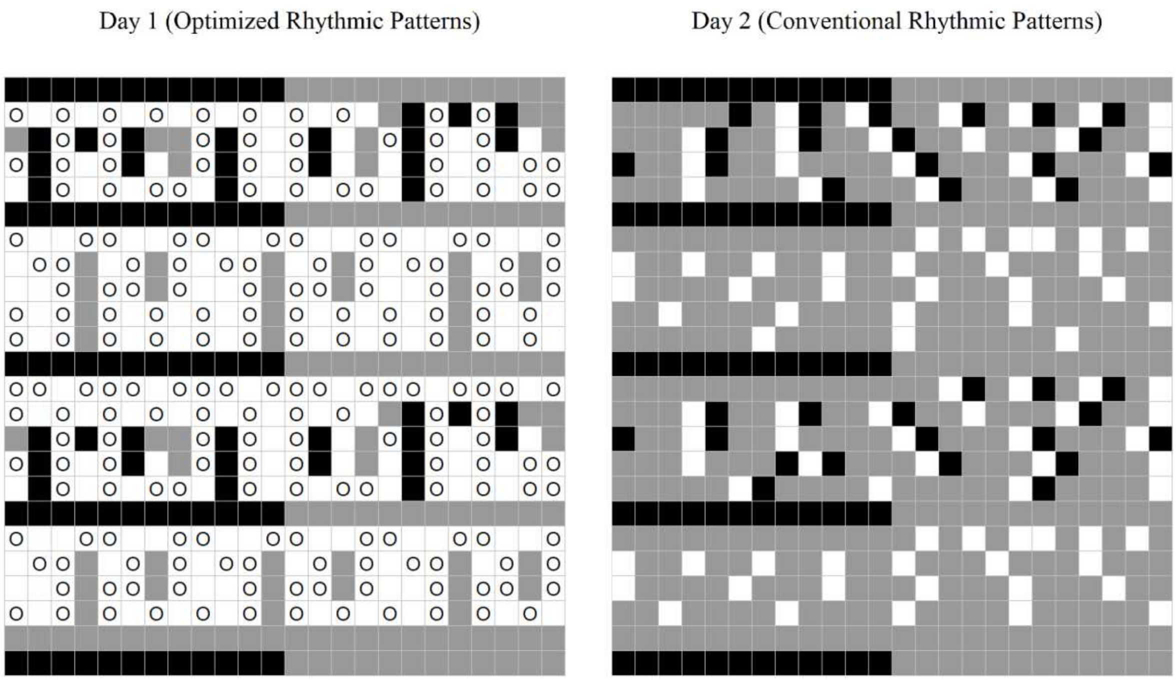


Figure 44: Rounds of day 1 (optimized RTM) and day 2 (conventional RTM) of Training 3

4.5.3.2 Execution of the 3rd Training

Three participants who already had taken part in Training 2 participated in this training. One new person was included. The performance files of ¾ of the participants were all usable, but even though I thought that the problem with the saving of the files (section 4.5.2.2) was solved, it turned out that it was not completely. Fortunately, I noticed this soon enough to tell all the participants what they could do to avoid this problem and all the files were usable for this training. One person skipped and missed rounds a few times and I solved this problem in the same way that I did for Training 2. In this case, I had to remove all the files of days 3 to 6 of this person and the rest was perfect.

4.5.3.2 Results of the 3rd Training

Figure 45: Results of Training 3 with 4 participants

Looking at the evolution of the performance values evolving in time in Figures 45, tendencies can be observed:

1) the performance of Part 4 of day 1 at the beginning (down to the right) weaker than for day 2 and becomes increasingly better over time;

2) Test 5 section has a better performance for day 1 during the whole training.

3) For all the other sections, the conventional methods proved to be better.

Results of Training 3 - 3 Participants

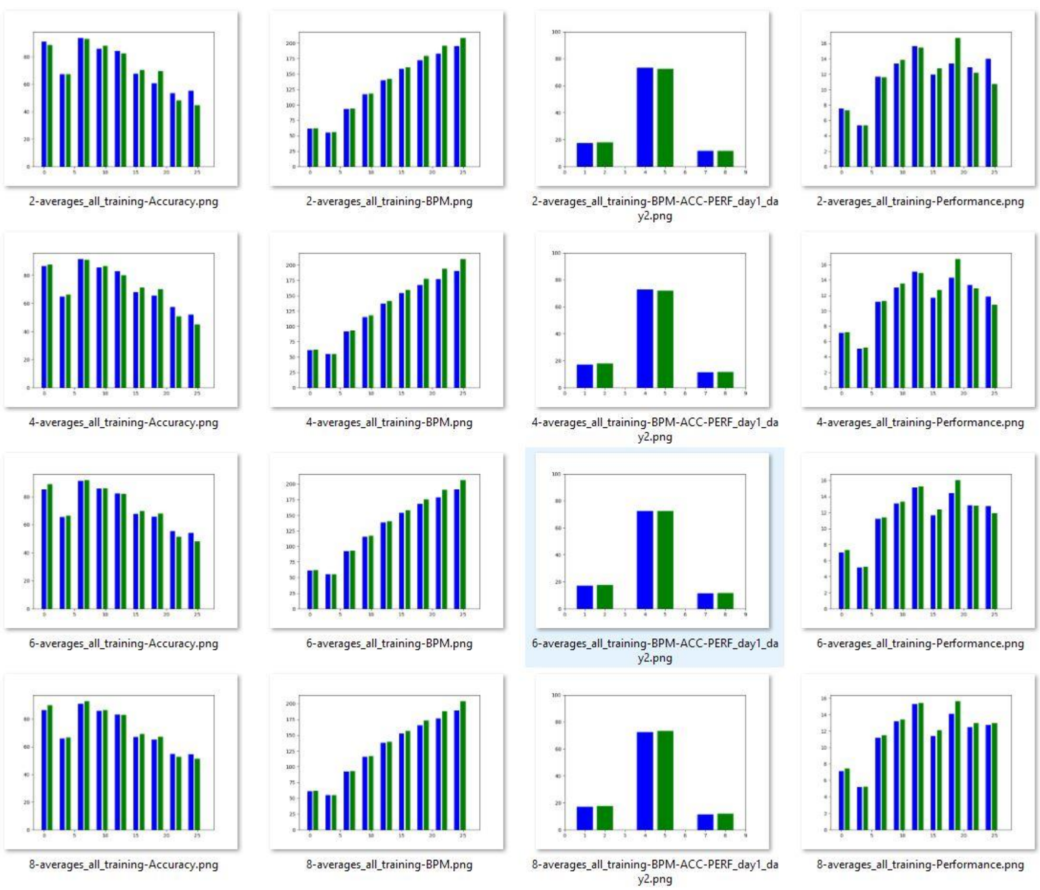


Figure 46: Results of Training 3 with 3 participants who also took part in Training 2

Analysing the results of the 3 participants who also did Training 2, the results show that:

1) At the beginning, the performance of all sections of day 2 and better than day 1.

2) As time progresses, all the sections except for Part 2, Part 3 and Test 4 sections become better for day 1.

Results of Training 3 - Ben

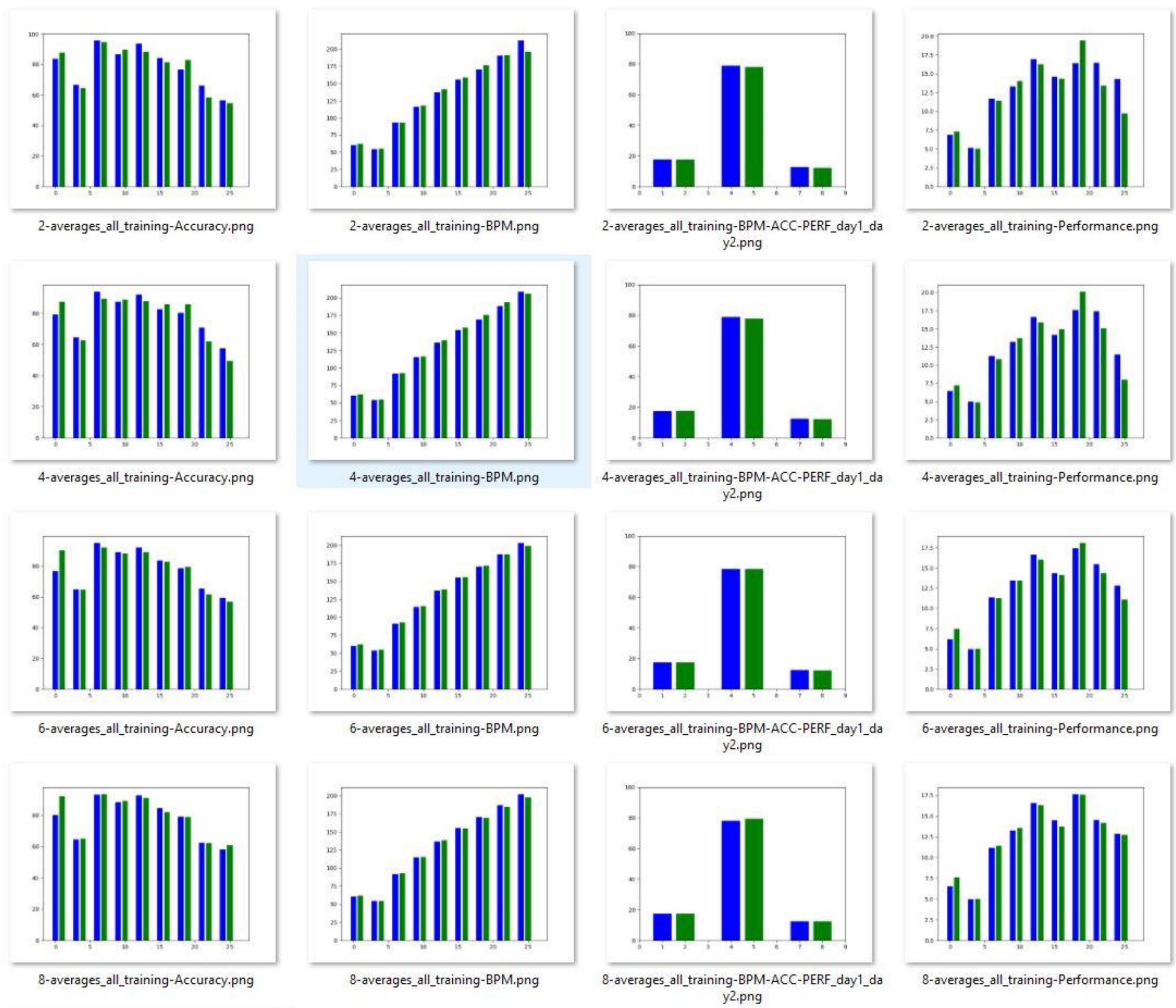


Figure 47: Results of Training 3 for participant with the pseudonym Ben.

Looking at the results of the participant with the pseudonym Ben, who plays both percussions and the keyboard and who also did Training 2, the following can be said:

1) The performance values for day 1 of the following sections increases over time and proved to be higher than results of day 2: Part 1 Test 2, Test 3, Part 3, Part 4 and Test 5.
2) In the Test 4 section, the performance of day 2 increase gradually and are higher than day 1.
3) Ben's high performance is to the fact that his accuracy stayed relatively high as the speed increased.

Chapter 5 – Results:

5.1 Evaluation of goals

List of all the goals

Goal	Result
1.2.1 Conception of the ARTA	
(M) Conception of the ARTA	Very successful
1.2.2 Adaptive mechanic	
(M) Implementation of an adaptive mechanic based on the results of a first 10 days training (section 1.2.5 – point 1)	Successful
(M) Analysis of the results of training 1 (section 1.2.5 – point 1) and 1st conception of a new RTM according to them.	Successful
1.2.3 Research about AI – Deep learning techniques	
(M) Research of AI techniques relevant for the project.	Very successful
(M) Generation of a data set with training performance data to train the ANN (at least 10 000 input data)	Very successful

(M) Conception, implementation and a 1st training of an ANN with the data generated through training.	Very successful
(S) 2nd training of an ANN with the new data with the same technique(s) as before or differently if necessary.	Not needed
(M) 2nd conception of a RTM: If the results show regular rhythmic patterns, I will conceive a new RTM according to the ANN's results.	Very successful
1.2.4 Research about human learning performance	
(M) Research in different fields in order to gain deeper and broader understanding of rhythmic training for the design of the ARTA.	Very successful
1.2.5 Evaluation of performance and RTM with the ARTA	
1. (M) Training 1 - Evaluation of my own performance with adaptive parameters and generation of data for the ANN.	Very successful
2. (M) Training 2 - Evaluation of the efficiency of all RTM with a comparative experiment, with at participants.	Very successful
1.2.6 Other goals	
(M) Get Regular feedback from supervisor and help from others.	Successful
(C) Generate more RTM then planned if possible.	Successful

I achieved all the necessary goals that I had planed for this project and went beyond the expectations, implementing extra evaluation features for the Training 1 and 2 and adding Training 3 to obtain results of better validity. In addition to the two conceptions of RTM, the first one being the adaptive mechanic-based tempo progression and the second, the new rhythmic patterns and their organization in rounds, I had the opportunity to analyse the results of Training 1 to fine-tune the round dispositions of Training 3. The only goal that I had intended to pursue decided not to do so, is the uploading of the performance data on an online database. This turned out to be unnecessary for the scope of this project and I decided to invest time in a more efficient solution: the performance folder structure described in section 4.1. It solved problems of internet security, saved CO_2 emissions and a lot of implementation and management time.

5.2 Summary and self-evaluation

In the light of this project, I can affirm with confidence that the three processes involved in the methodology, self-evaluation, adaptive mechanics and machine learning techniques successfully led to the generation of new rhythmic training methods that proved to be more efficient than conventional ones in regards of reaching the best performance possible in the shortest training time. Self-monitoring was useful to monitor the performance in an intuitive way that cannot be measure or analysed with computers, but since the RTM used in this project are used by humans and not computers, it was relevant to bring it useful experience about the performance in the global equation. The adaptive mechanic was used to find out new tempo progression patterns and it was calculated that a ratio of approximately 2:1 (0.52), where the frequency to modify the tempo in number of beats should be 2 times greater than the bpm increasing value. This ratio proved to be efficient at building speed during the training sessions, but also over time, from day 1 to 10 of the trainings. This was also true for the performance, but less significantly. Figure 48 shows the progression of speed average of each round over time during Training 2 with four persons, where the X axis is the bpm values and the Y axis, the number of rounds in chronological order. Figure 49 shows the same progression for the performance.

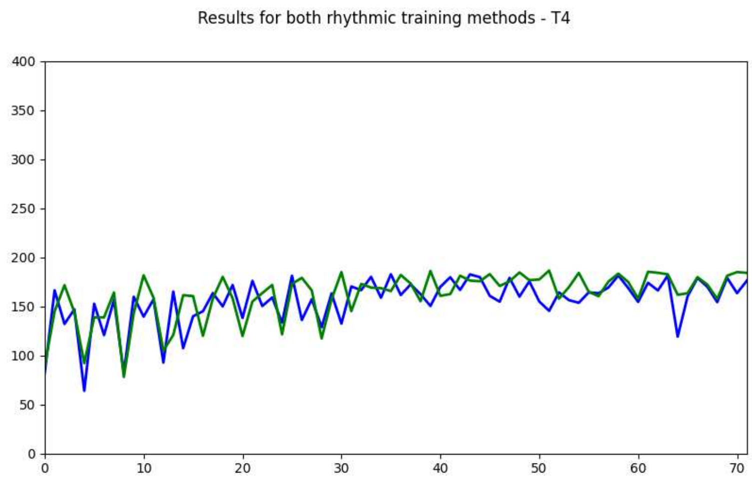


Figure 48: Evolution of the bpm value during Training 2 – in blue: new RTM; in green: conventional RTM

Figure 49: Evolution of the performance value during Training 2 – in blue: new RTM; in green: conventional RTM

The new rhythmic patterns that were discovered and implemented in those trainings were successfully generated by the predictions of the artificial intelligence and the best type of neural network that was used for this purpose in the Bilateral Long Short-Term Memory with the use of time window shaped X data set.

The evaluation trainings were designed on the basis of one-group pretest–posttest comparative experiment design and could deliver some results concerning the performance within training rounds, but could shed no light on the importance of cross learning effects from day to day.

Self-reflection:

In my project plan, |I had planned to work on the adaptive mechanic before the AI, but it turned out that the processes were so related, that it made sense to combine those processes and execute them in parallel, because a good understanding of the AI was required to structure the adaptive mechanics and even the conception of the round structures that shaped the performance files was dependant on the knowledge of how the AI worked.

Concerning the adaptive mechanics, to calculated the best adaptive parameters, I considered the best performances achieved during Training 1. This seemed to make sense and it proved to be efficient at building speed over time within rounds. This was often done at the cost of accuracy and it seemed to me that the increasing rate of the tempo was too high. Some of the participants said that their hand was very tight and stressed when the tempo became fast for them. I hypothesize that the calculation of such progression curve should be done in a wider time context, perhaps, of several months and not only 10 days.

The AI part of the project went very well and I used the techniques that I found realistic for me to learn in the context of this project. The process concerning deep-learning of the methodology of this proof of concept could probably be done with more advanced machine learning techniques, to achieve even better results.

What I would do differently if I was to start over is to spend more time searching for experts in the field of machine learning, because it is a complex subject and the advices I got from my friend who is software engineer allowed me to progress faster and have more assurance.

Looking back at the evaluation of RTM, I think that further research involving three groups (control, conventional RTM and new RTM) and more people would allow a better understanding of why some of the new RTM in this project were associated with better performance as conventional ones. It would be interesting for future research to push the experiment further by recording brain waves with EEG during participant's performance to see whether and how the new RTM impact the theta brain waves because of the Zoom-in technique. Something very interesting that I discovered during my research in different fields, is that some of the patterns that I had already implemented seem can be found in Mozart's K.41 used in a study of the Mozart effect mentioned in chapter section 2.1.2.2, which I did not take any rhythmic pattern from for this project, but it would be very interesting to integrate more of Mozart's music in future research. The following musical sections contain patterns discovered by the ANN:

Figure 51: Mozart's K.41 – page 1(musopen.org, 2022, p.2)

Figure 50: Mozart's K.41 – page 1(musopen.org, 2022, p.1)

Figure 52: Mozart's K.41 – page 1(musopen.org, 2022, p.4)

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Figure 53

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Annex 1

EEG Experiment – Temporal Exploration in Covert Attention Movement

The Zoom-in Technique

This experiment was done to observe the effects of the Zoom-in technique described in section 2.4.3. Here are the EEG results of the control states and exercises, where the attention was focused on the pace of a metronome at different tempo on different rhythmic patterns:

EEG Alpha-Theta Waves Experiment

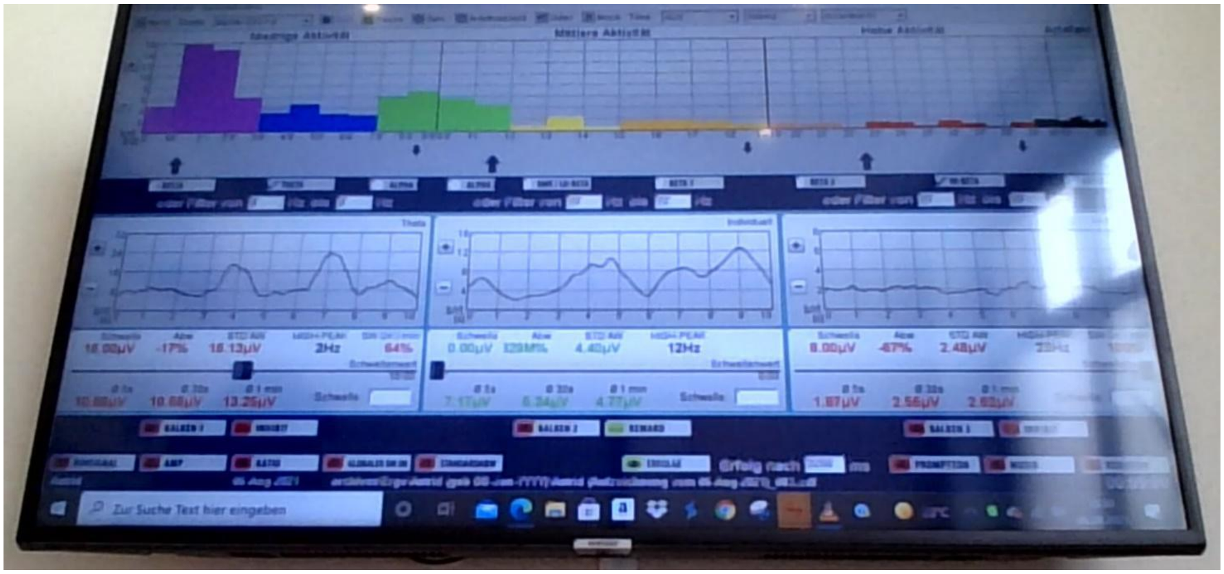
Task	*BPM*	*Rhythmic Pattern*	*Spatial pattern*	*Total time*	*Mode*	*Silence value*	*Previous pause lenght*	*Comment*
Control 1	*50*	-	*Whole body*	*15sec*	*No accent*	*15sec*	*15 sec*	
Control 2	*50*		*L thumb tip*	*15 sec*	*No accent*	*15 sec*	*15 sec*	
Control 3	*50*		*L toe tip*	*15 sec*	*No accent*	*15 sec*	*15 sec*	
1	*50*		*L thumb* < - > *R thumb*	*30 sec*	*No accent*		*15 sec*	
2	*50*	+ -	*L thumb* < - > *R thumb*	*30 sec*	*L accent*		*15 sec*	
3	*50*	- +	*L thumb* < - > *R thumb*	*30 sec*	*R accent*		*15 sec*	
4	*50*	+ - -	*L thumb* < - > *R thumb*	*30 sec*	*alternate*		*15 sec*	
5	*50*	+ - - -	*L thumb* < - > *R thumb*	*30 sec*	*R accent*		*30 sec*	
6	*60*		*L thumb*	*30 sec*	*No accent*		*15 sec*	

			< - > R thumb					
7	60	+ -	L thumb < - > R thumb	30 sec	L accent		15 sec	
8	60	- +	L thumb < - > R thumb	30 sec	R accent		15 sec	
9	60	+ - -	L thumb < - > R thumb	30 sec	L accent		15 sec	
10	60	+ - - -	L thumb < - > R thumb	30 sec	R accent		30 sec	
11	50		L thumb < - > R thumb	30 sec	No accent		15 sec	
12	50	+ -	L big toe < - > R thumb	30 sec	L accent		15 sec	
13	50	- +	L big toe < - > R thumb	30 sec	R accent		15 sec	
14	50	+ - -	L big toe < - > R thumb	30 sec	L accent		15 sec	
15	50	+ - - -	L big toe < - > R thumb	30 sec	R accent		30 sec	
16	60		L big toe < - > R thumb	30 sec	No accent		15 sec	
17	60	+ -	L big toe < - > R thumb	30 sec	L accent		15 sec	
18	60	- +	L big toe < - > R thumb	30 sec	R accent		15 sec	

19	*60*	+ - -	*L big toe < - > R thumb*	*30 sec*	*L accent*		*15 sec*	
20	*70*		*L thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 1 pattern 1 bar*	*15 sec*	
21	*80*	+ -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 1 pattern 1 bar*	*15 sec*	
22	*90*	- +	*L thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 1 pattern 1 bar*	*15 sec*	
23	*100*	+ - -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 1 pattern 1 bar*	*15 sec*	
24	*70*		*R thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 2 patterns 2 bar*	*15 sec*	
25	*80*	+ -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 2 patterns 2 bar*	*15 sec*	
26	*90*	- +	*L thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 2 patterns 2 bar*	*15 sec*	
27	*100*	+ - -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 2 patterns 2 bar*	*15 sec*	

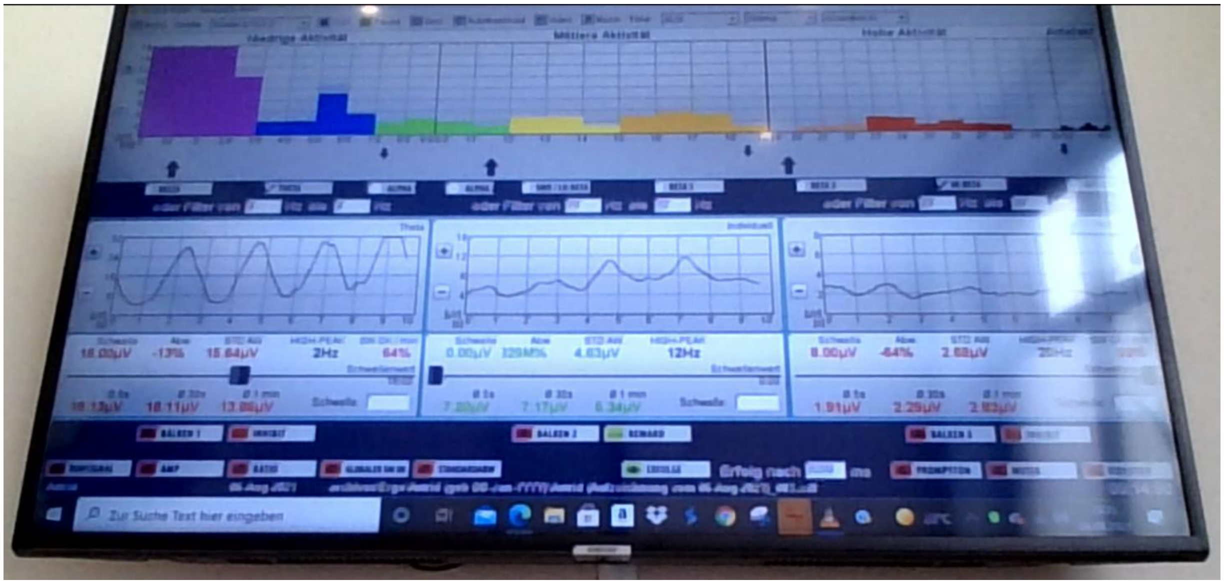
28	*110*		*L thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 4 patterns 4 bars*	*15 sec*	
29	*120*	+ -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 4 patterns 4 bars*	*15 sec*	
30	*130*	- +	*L thumb < - > R thumb*	*30 sec*	*L accent*	*+ still 4 patterns 4 bars*	*15 sec*	
31	*140*	+ - -	*L thumb < - > R thumb*	*30 sec*	*R accent*	*+ still 4 patterns 4 bars*	*15 sec*	

Control 1:



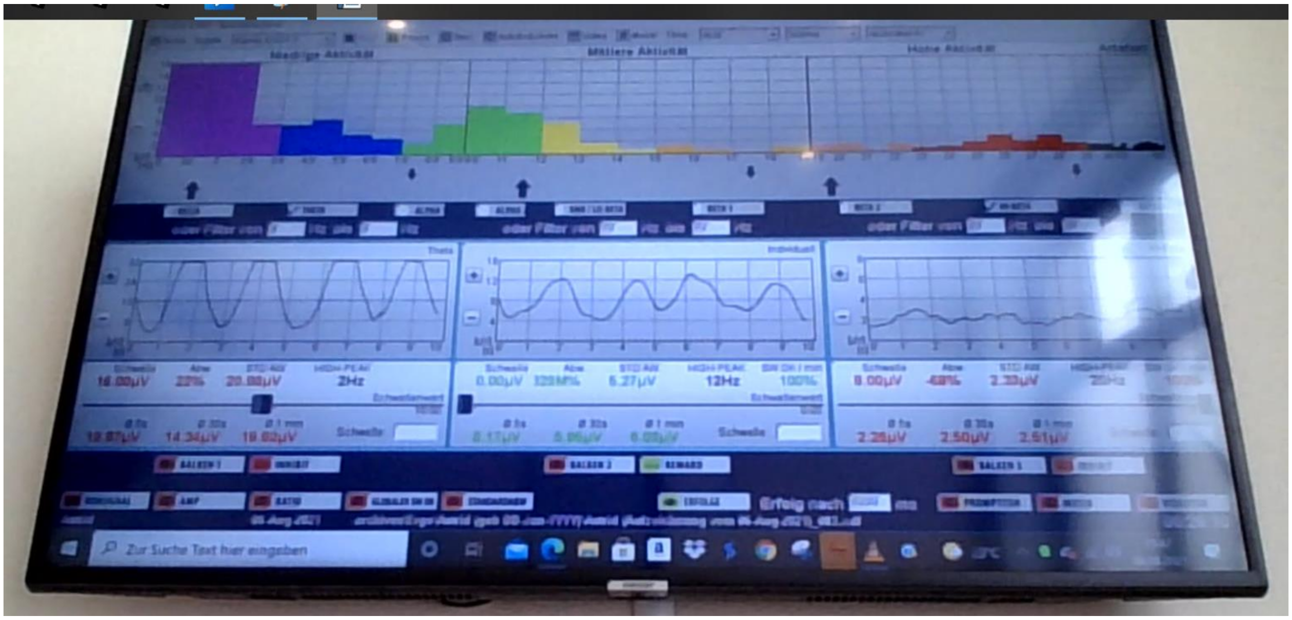
Exercise 2:

Exercise 3:



Exercise 5:

Exercise 12:



Exercise 20:

Exercise 26: