TALLINN UNIVERSITY OF TECHNOLOGY
School of Information Technologies
Department of Software Science

Rahel Rjadnev-Meristo 122305IAPM

FINE MOTOR ANALYSIS FOR SCHOOL SUCCESS AND HABITS MODELLING OF SCHOOLCHILDREN

Master's thesis

Supervisors: PhD Sven Nõmm
PhD Aaro Toomela
Consultant: PhD Birgy Lorenz

Tallinn 2018

TALLINNA TEHNIKAÜLIKOOL
Infotehnoloogia teaduskond
Tarkvarateaduse instituut

Rahel Rjadnev-Meristo 122305IAPM

KOOLILASTE PEENMOTOORIKA ANALÜÜS ÕPPEEDUKUSE JA HARJUMUSTE PÕHJAL

magistritöö

Juhendajad: PhD Sven Nõmm
PhD Aaro Toomela
Konsultant: PhD Birgy Lorenz

Tallinn 2018

Author's declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

Author: Rahel Rjadnev-Meristo

10.05.2018

Abstract

This thesis investigates whether hobbies, habits, moods, tiredness, learning style and success at school influence fine motor abilities. A device called Leap Motion was used to capture the hand movements. An application for executing pattern drawing exercises and recording hand data was developed. Participants were asked to fill a questionnaire for finding out the learning style and give rough estimations about the frequency of certain hobbies, habits, and a personal assessment of their current mood, tiredness, and success at school. Movement smoothness parameters (motion mass) and drawing precision are calculated based on the recorded data. Classifying machine learning methods are applied to find out any relation between the calculated parameters and answers. Several weak relations were detected and decision trees sufficiently predicted about half of the answers.

This thesis is written in English and contains 57 pages of text, 5 chapters, 24 figures, 17 tables.

Annotatsioon

Koolilaste peenmotoorika analüüs õppeedukuse ja harjumuste põhjal

Käesolev magistritöö uurib, kas hobid, harjumused, tuju, väsimus, õpistiili ja õppeedukus mõjutavad peenmotoorikat. Käeliigutuste mõõtmiseks kasutati seadet nimega Leap Motion. Mustrijoonistusharjutuste läbiviimiseks ja andmete salvestamiseks arendati rakendus. Osalejatel paluti täita küsimustik, et teada saada nende õpistiil, anda umbkaudne hinnang teatud hobide ja harjumuste sageduse, tuju, väsimuse ja õppeedukuse kohta. Salvestatud andmete põhjal arvutati liigutuse sujuvuse parameetrid (liigutuste mass) ja joonistuste täpsus. Arvutatud parameetrite ja vastuste vaheliste seoste leidmiseks kasutati klassifitseerivaid masinõppe meetodeid. Mitu nõrka seost tuvastati ning otsustuspuud ennustasid piisava täpsusega umbes pooli vastuseid.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 57 leheküljel, 5 peatükki, 24 joonist, 17 tabelit.

List of abbreviations and terms

DTW	Dynamic Time Warping
LM	Leap Motion

Contents

List of Figures

List of Tables

1 Introduction

Present work is devoted to the studies on fine motor performance with respect to the habits, hobbies, mood, tiredness, and learning styles. The goal is to investigate the influence of these aspects on fine motor performance.

The thesis is organised in the following way: introduction chapter highlights related work, explains the background and presents a formal problem statement. Second chapter describes the experimental setting and methodology: the hardware used, the software written for carrying out the tests and gather data, the questions asked from the participants, and how the data was analysed. Third chapter lists the main results acquired from analysis. Fourth chapter discusses the obtained results and problems. Fifth chapter concludes the work and outlines possible future opportunities.

1.1 Related work

A study [1] investigating the relations between arousal and locomotion smoothness established that the state of mind and motor functions are connected.

Motion mass was proposed in [2] and [3] as a way to describe the state of motor functions and measure changes.

Using motion mass, main interest has been on assessment of neurodegenerative illnesses and learning. Several classical Parkinson's diagnosis test were digitised, motion mass calculated and the data analysed with machine learning: Luria alternating series tests in [4], Poppelreuter figure visual perceptual function test in [5], clock drawing test in [6]. Spiral drawing was proven as well as an effective way to diagnose Parkinson's in [7]. Learning-focused studies were [3] and [8].

In [2], and Microsoft™Kinect™was used to take the measurements and analyse gross motor function. In [4], [5] and [6], tracking of fine motor was required, so the data was acquired by tracking the pencil drawing on a tablet.

For this thesis, Leap Motion (LM) was selected as the sensor as it tracks the whole hand, enabling analysis of fine motor functions. In addition, it is easy to set up, portable and inexpensive. There is much interest towards this small device. After a study [9] investigated its actual accuracy, many new ideas about possible applications were generated.

LM has been used in training to prepare medical students for surgery in [10] and [11], assessing the state of Parkinson's patients in [12] or the range of joint movements in [13]. Other medical uses include improving rehabilitation after a stroke by monitoring hand gestures [14], the finger pair movement exercise [15] or speed up recovery playing games in [16].

Recognising sign language has been a complex problem, and Leap Motion has been helping to solve it little by little, starting with a subset of Chinese sign language [17], and continuing with Arabic [18], Indonesian [19] [20], manual signs and fingerspelling in [21].

Leap Motion can also be used to identify people based on their hand tremor [22], input syllables [23] or numbers [24], control robots [25] and quadrocopters [26], automatically make a task more difficult to keep up the progress of learning [8], and carry out a puppet show [27].

1.2 Linked studies

Our department has done a lot of research on the topic of motor functions, figure 1.1 illustrates relations between them. White nodes represent completed work, blue nodes represent work in progress and green node represents the current thesis.

First important work of our department in this area was done as a bachelor's thesis by Mihhail Lapuškin in 2009, which was "Application for Control of the "Pioneer"

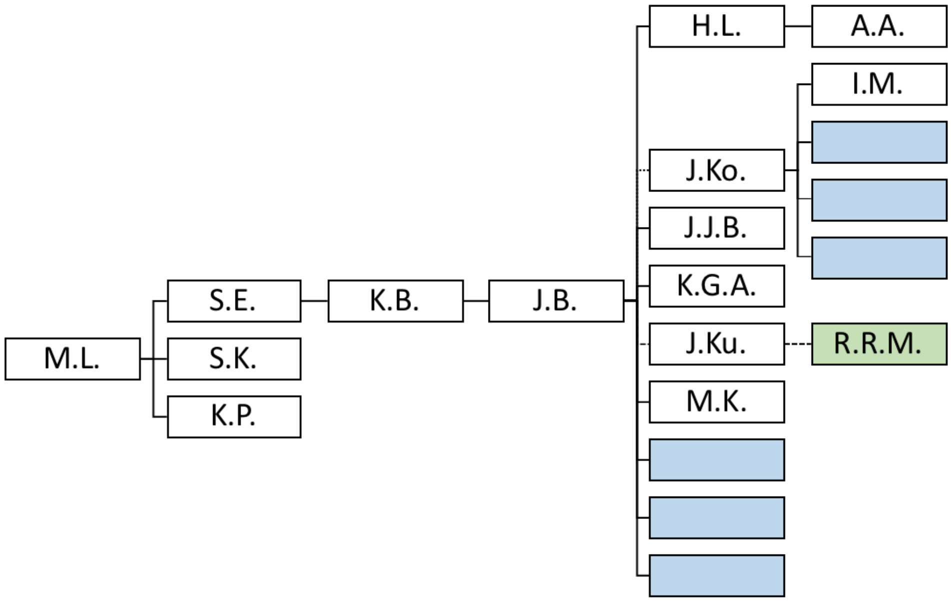


Figure 1.1: Relations between the motor function studies in our department.

Robot with Manipulator" [28]. He added gestures and developed the topic further, writing a master's thesis in 2012, "Application for Gesture Based Control of the "Pioneer" Robot with Manipulator" [29].

His work was followed by three papers: "Scrub Nurse Robot voting automata for detecting and learning motions" [30] by Kenno Parm (K.P.) in 2010, "Recognition of Hand Gestures Using Bezier Curve and K-nearest Neighbors Method" [31] by Siim Kirme (S.K.) in 2016, and "Gesture Based PC Interface with Kinect Sensor" [32] by Samet Erap (S.E.) in 2012.

Samet Erap also developed the first prototype that saved the data from Kinect to files. That program initiated a whole array of new theses. First of those was "Monitoring of the human motor functions rehabilitation by neural networks based system with Kinect sensor" [33] by Kirill Buhhalko (K.B.) in 2013. It was followed by "Alternative Approach to Model Changes of Human Motor Functions" [3] by Jevgeni Boruško (J.B.) in 2014.

Based on this work, many new papers has been written. First was "Multi-Kinect system for acquisition of turning motion" [34] by Helena Lissenko (H.L.) in 2015, which was used to write "Low cost gait capture during turning motion" [35] by

Ahmed Abdelhady (A.A.) in 2017.

During the same year, validating the Kinect data was simplified with “Correctness Analysis of Captured Skeleton Model” [36] by Kris-Gerhard Aabrams (K.G.A.) and a program to recognise and calculate movement parameters for the “Up and go” and similar tests using Kinect was developed in “Context Based Registration and Analysis of Human Motions” [37] by Jan-Joonas Bernstein (J.J.B.).

The first paper to diagnose based on motor functions was “Quantitative Analysis of the kinematic features for the Luria’s alternating series test” [4] by Julia Koženkina (J.Ko) in 2016 and she used a tablet to record the fine motor movements for analysis. Analysing the fine movements also enabled digitising the clock drawing test in “Digital clock drawing test implementation and analysis” [6] by Ilja Mašarov (I.M.) in 2017.

The first thesis that utilised Leap Motion in our department was “Gesture evaluation for Leap Motion” [38] by Maria Kohtla (M.K.) in 2015 where gestures and drawn lines were evaluated. The second paper was “Virtual reality aided framework for modeling changes in finger motion and orientation during learning fine motor activity” [8] by Jaroslav Kulikov (J.Ku.) in 2017 and it used LM to detect successful learning of stacking objects and automatically make the task more difficult.

This thesis is the third in our department to use LM and is mostly based on the work of Jevgeni Boruško, but also related to the previous Leap Motion papers and Julia Koženkina’s work with Luria alternating series tests.

As seen on the figure, there are several papers in progress at the moment, all of them focusing on investigating motor functions.

1.3 Background

Motor system is the part of central nervous system that guides the voluntary movements. A.R. Luria studied frontal lobes and voluntary movements and stated in his research [39] that intentional movements consist of several stages:

- a goal is set
- planning: why and how in general the movement should be done
- specifying: the details and patterns of the movement
- signals are sent through the spine
- the result is assessed

Luria alternating series tests are meant to affect different stages of a motion lifecycle. Constantly switching patterns forces the change of plans since it is easier to keep drawing the same pattern. For that, the PL test was created - drawing squares and triangles in turn, as one line.

Another aspect of Luria's tests was the amount of available guidance, meant to find out which stage of the motion execution a disorder affects:

- trace - draw atop the example
- copy - draw the same pattern below the example
- continue - continue the example, using the same pattern

Completing all but the easiest test might indicate difficulty recognising the assisting nature of the example. Having significant difficulty with only the third test hints at issues with generating the patterns for movement. Failing all the tests indicates issues with sending signals through the spine.

1.4 Problem statement

The goal of this thesis is to investigate relations between fine motor functions and certain aspects of a person. Which kinetic parameters would reflect the mood, hobbies and habits, tiredness, learning style, activities already done that day, and how would one estimate personal success at school. Would it be possible to construct decision trees that predict these values.

This leads to a number of sub-problems to be solved:

- Data gathering
- Data processing
- Selecting attributes
- Training classifiers

For acquiring the fine motor data, suitable software with the purpose of presenting tasks and recording data will be developed. It will interface with Leap Motion to provide constant feedback to the user and store the data for later analysis. People will complete the exercises and fill a questionnaire asking about their mood, hobbies, habits etc.

As preparation for analysis, the fine motor data needs to be anonymised, arranged by pattern into smaller subsets, and have motion mass and Dynamic Time Warping (DTW) calculated for each test and subset.

Z-test validates whether each group formed by a question, its answer and motion parameter is different enough. For each combination of questionnaire answer and motion parameter, correlations are calculated. Fisher score is calculated for labeled answers. Pearson correlation coefficient is calculated for numerical answers.

Classifiers will be trained with the most correlated combinations. Chosen machine learning methods include decision trees, AdaBoost, gradient boosting and support vector machine.

2 Experimental setting and methodology

Leap Motion was used to capture the hand data. Special software was developed for carrying out the tests and analyse the data.

2.1 Leap Motion

As described on the product site [40], Leap Motion is a small device that consists of three LEDs (Light-emitting diode) and two infrared cameras, giving it a wide detection area. The captured images are streamed as a greyscale stereo image via USB (Universal Serial Bus) to the Leap Motion Service which then reconstructs a 3-dimensional representation of the image. Helper libraries organise and stream the data in a structured manner, providing access to a short history of model frames.

A study [9] measured the average dynamic accuracy to be 1.2mm and standard deviation in X, Y and Z axes to be about 0.5 mm, above 1.0 mm and below 1.0 mm, respectively.

A frame contains data of each detected hand, providing location and direction of each bone and joint. The software applies its internal model of a human hand, visible parts and past observations to calculate the most likely positions for parts that are not visible at that moment. A confidence rating with values between 0 and 1 indicates how well the observed data fits the internal model [41].

Distance, time, speed and angle values are provided in the following units, millimetres, microseconds, millimetres/second and radians. A right-handed Cartesian coordinate system is used. The origin is at the top of the Leap Motion controller. Locations and directions of the axes are displayed in figure 2.1.

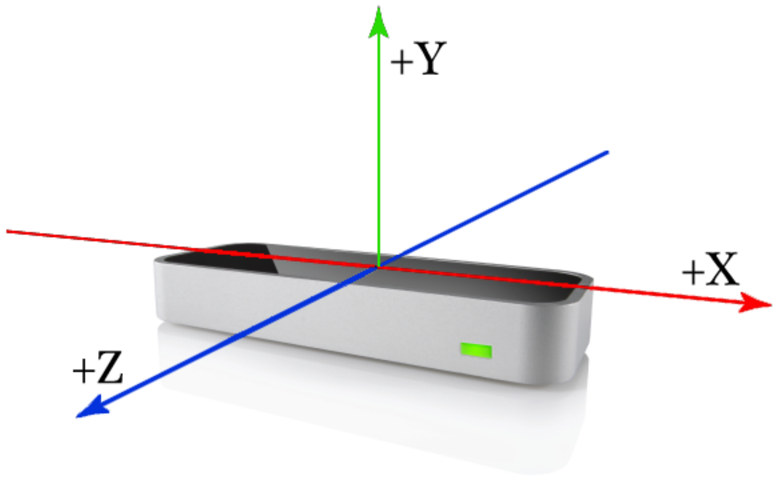


Figure 2.1: Axes positioning on the Leap Motion controller [41].

2.2 Data gathering program

In order to gather data, a program was developed that would guide the user in completing certain tasks and then write the LM measurements to a file.

2.2.1 Technologies

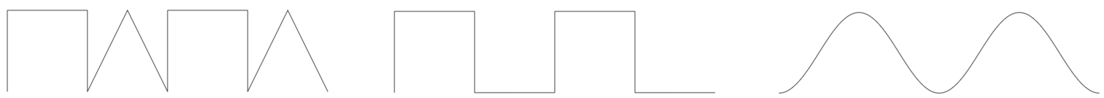
The program was written using JavaScript, HTML (HyperText Markup Language), CSS (Cascading Style Sheets) and Electron. JavaScript was chosen because Leap Motion has decent support for it and the author is most familiar with web development and creating user interfaces with CSS and ReactJS. LeapJS is a library for JavaScript to provide access to the LM data. Electron was used to package the web app as a standalone program.

2.2.2 Organization and tests

The program flow asks for identification code, then continues to a pre-fixed test. After test completion it shows how many tests are made and how many are left.

After a few seconds, the next test is started. A countdown timer is displayed to give a sense of the flow and explain why a screen changes on its own. The program loops until all tests are completed after which it will ask for a new participant and identification.

Each test consisted of tracing a line on the screen with the index finger tip. Draw tests have two subtypes: trace and continue. “Trace” means that the pattern repeats four times as seen in figure 7, and the subject needs to draw directly on it. “Continue” means that the pattern appears only once and the subject needs to draw on it and then continue drawing the pattern without a guide. The patterns are: PL, PP, and sine wave (examples on figure 2.2)



(a) PL pattern. (b) PP pattern. (c) Sine wave pattern.

Figure 2.2: Examples of patterns.

The tests try to visualise drawing. There is a circle that signifies the current location and a line is left behind when the circle is moved.

Each test contains an introduction and an execution phase. Each drawing test starts with preparation. The user can learn the connection between their hand and a cursor on screen. When ready, aim the cursor at the “start” area and wait about 1 second. Then the board is cleared of past lines and serious drawing can start. At the end, there is again a small wait area the user has to aim at in order to complete the test.

2.3 Data gathering process

The participants were children in ages between 8 and 13. Out of the total 160 participants, 138 completed both tests and questionnaires. The tests were carried out at school, during computer lessons. The parents were asked for permission.

Initially, names were used to match the test and questionnaires since they had different sources, afterwards the names were removed.

2.3.1 Questionnaires

Firstly, each participant was asked to complete two questionnaires. The first one was about finding out the participant's learning style. The other one was about one's hobbies, habits, mood and tiredness of that particular day.

The learning styles test [42] contained 30 questions and possible answers were "rarely", "sometimes" and "often". This test was chosen because it was in native language for the participants, aimed for schoolchildren, publicly available and easy to use. The result was immediately displayed immediately after submitting the form. The aim of this test was to find out if there is any correlation between learning modalities and fine motor test results.

The second test contained 19 questions and possible answers to most of the questions were:

- 1 - not at all
- 2 - rarely
- 3 - sometimes
- 4 - often
- 5 - very often

There were four general topics: habits, hobbies, ease of learning and current tiredness. Versions in the original language are listed in appendix B.

Habit and hobby questions were meant to find out if the participant engages in activity that could influence visual, auditory, logical or motor skills:

- I play computer or console games in my spare time
- I do sports in my spare time

- I dance in my spare time
- I use the smartphone for communication
- I use the smartphone for playing
- I solve logical problems (e.g. sudoku) in my spare time
- I talk to my friends in English
- I draw/doodle
- I sing on my own

Learning questions were for estimating how good the participant feels about one's learning skills:

- I can complete all the exercises during the mathematics class
- I feel that studying goes well
- I feel that it is easy for me to learn (take part in class, complete tasks, do homework)

Tiredness questions were for estimating the general mood and how tired the participant could already be at the moment of the tests:

- It is easy for me to wake up in the morning
- Today I have already done something on my smartphone that needs finger dexterity (games, typing)
- Today I have already written on paper
- Today I have already done/built something with my hands
- Today I feel sad/happy (in the scale of 1 to 5, sad is 1 and happy is 5)
- Today I feel tired/lively (in the scale of 1 to 5, tired is 1 and lively is 5)
- Yesterday I fell asleep at about <time>

2.3.2 Test execution

At the start of the lesson everyone was told that there are three tasks, two questionnaires and a test. Then everyone was invited to gather around the author who would show the device, how it works and how the program works. The tests were carried out with the participant sitting behind a desk. The computer and Leap Motion were positioned on the far side of the desk, giving enough room for comfortable drawing.

The data gathering program first presented 12 drawing tests in a row for each participant. Each test type was repeated three times. The first three test sets were tracing and the last one was continuing. The trace tests, in execution order, were PL, PP, and sine. The last continue test was again PL.

In order to gather more data during the limited time, three pairs of LM devices and computers were set up. After a participant was done with the test series, next volunteer was called. At the signs of frustration, the author reassured that it is normal to experience difficulty.

2.4 Gathered data

Leap Motion generated data at the rate of 50 to 110 frames per second. Each frame was written as one row to a CSV (comma-separated values) file. Each new test generated a new file, creating 12 files per participant.

Each LM frame contains locations and directions of each joint and bone, dimensions of each bone, grab and pinch strength, sphere location and radius, left or right hand, is finger extended or not, how long has the hand been visible, hand model confidence, and microseconds since the device was connected.

To keep the scope of the thesis reasonable, only wrist position and index finger tip position was analysed. All gathered data is anonymised. The rest was saved for future research.

2.5 Data analysis

Special software was developed in Python 3.6 to perform data analysis, using SciPy, NumPy, Scikit-learn [43], dtw [44] and Matplotlib libraries.

2.5.1 Motion parameters

Motion Mass [2] is used to measure amount and smoothness of a movement. When learning a new motor activity, movement becomes more precise and smooth with practise. Motion mass is calculated for each text execution and has 5 components: combined Euclidean distance, trajectory mass, velocity mass, acceleration mass, jerk mass. In addition, ratio between acceleration mass and time was calculated.

For each test, DTW (Dynamic Time Warping) was calculated. It is used in time series analysis to measure similarity between two temporal sequences which may vary in speed, such as video, audio, or any other data that can be turned into a linear sequence. As DTW calculates an optimal match between two sequences, their similarity is independent of certain non-linear variations in the time dimension. Guide patterns had number of points adjusted according to the data size.

Since there were 4 repetitions of each pattern, each data set was arranged into cycles. Motion Mass and Dynamic Time Warping (DTW) was calculated for each test, both as the full suite and separately for each cycle. Motion mass data and questionnaire answers were matched together. Analysis was carried out on that data.

2.5.2 Analysis methods

Z-test and p-values were calculated for each answer of a question and motion parameter combination, splitting the data into two groups by those who answered “A” and those who did not.

There were two types of answers, numerical and classifiers. Most numerical responses ranged on the scale of 1 to 5, such as “I use my smartphone for communication” or “I feel sad/happy”. Classifiers could not really be ordered, for example learning styles, which had answers like “Visual”, “Auditory”, “Kinesthetic”, “Undefined” and combinations of the first three, such as “Auditory, Visual” and “Kinesthetic, Visual”.

Fisher score was used to find combinations of motion mass field and answers where the value of an motion mass calculation could predict the answer. It was used for both numerical and classifier answers in case the correlation is not linear.

Pearson correlation coefficient was used to find any linear correlation between the motion mass calculations and numerical answers.

Using the parameters with best Fisher scores for each answer, decision tree classifiers and tree boosters were trained. Results were checked with cross-validation which split data with K-fold.

Since K-fold required at least k representations of each answer and some answers were too weakly represented, “very rarely” - “rarely” and “often” - “very often” were equalised.

3 Main results

Distribution of the answers is displayed in appendix C.

All results express relations between motion parameters and answers. Since both have long names, they have been abbreviated for an easier overview.

The habit, hobby, and other questions are abbreviated to the most distinctive word:

- Dancing - I dance in my spare time
- Sports - I do sports in my spare time
- Phone communication - I use the smartphone for communication
- Phone playing - I use the smartphone for playing
- Solving logical - I solve logical problems (e.g. sudoku) in my spare time
- Drawing - I draw/doodle
- Complete in maths - I can completer all the exercises during the mathematics class
- Studying goes well - I feel that studying goes well
- Learning is easy - I feel that it is easy for me to learn (take part in class, complete tasks, do homework)
- Easy morning wakeup - It is easy for me to wake up in the morning
- Dexterity used - Today I have already done something on my smartphone that needs finger dexterity (games, typing)

- Built with hands - Today I have already done/built something with my hands
- Sad/happy - Today I feel sad/happy (1 - sad, 5 - happy)
- Tired/lively - Today I feel tired/lively (1 - tired, 5 - lively)

The motion parameters contain a lot of details, indicating the calculated value, joint, test and cycle.

For example "**velocity mass, relative index tip Z, test 7, cycle 4**" expresses that:

- velocity mass - the motion mass parameter is velocity mass
- relative - the location of joint is not relative to Leap Motion, but to wrist
- index tip - the joint in question is tip of index finger
- the axis under observation is Z (depth)
- test 7 - the parameter was calculated using data from the 7th test
- cycle 4 - the calculation used data from only the 4th cycle

Furthermore, test and cycle ordering are fixed. The number and test map is displayed in table 3.1. Cycle numbers have the following meanings: 1 to 4 are the four repetitions, 5 is the data captured after the last pattern is finished, since recording continues while participant is aiming the cursor at the ending area.

Table 3.1: Test order

Index	Test name	Index	Test name
1	1st PL tracing test	7	1st sine tracing test
2	2nd PL tracing test	8	2nd sine tracing test
3	3rd PL tracing test	9	3rd sine tracing test
4	1st PP tracing test	10	1st PL continuing test
5	2nd PP tracing test	11	2nd PL continuing test
6	3rd PP tracing test	12	3rd PL continuing test

3.1 Examples of drawings

Here are some good examples of drawings done by the participants, visible in figure 3.1. The pattern they tried to follow is in orange, and their actual result is in blue.

PL_trc means that it was PL pattern tracing. PL_cnt represents the PL continuing task - pattern is shown only once and the rest had to be drawn without any help. Parentheses show the index of the test, (10) indicating the 11th test.

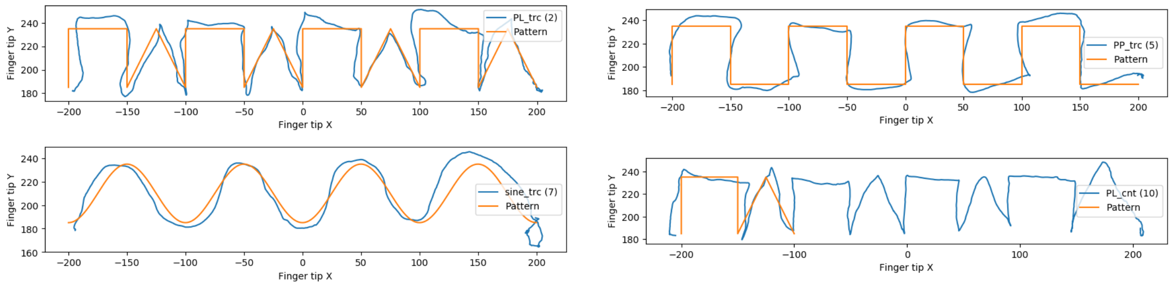


Figure 3.1: Well-drawn examples.

Sometimes the pattern was not followed very closely (3.2).

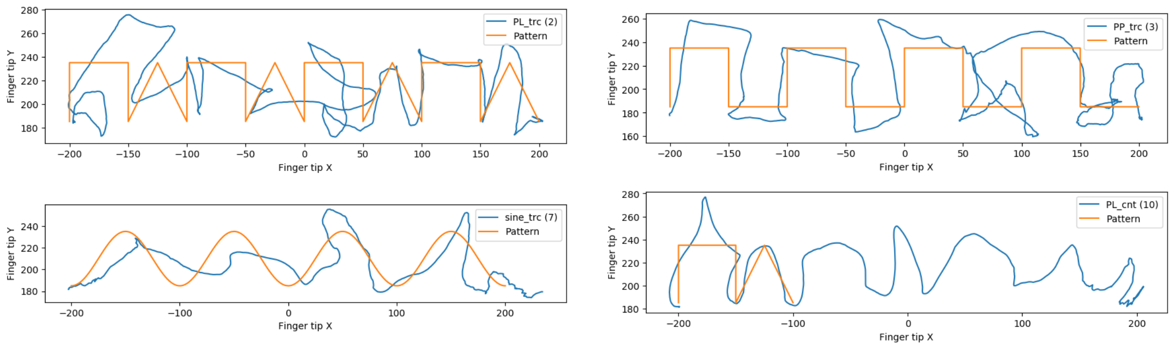


Figure 3.2: Less accurate examples.

3.2 Statistical hypothesis testing

Statistical hypothesis testing is used to find out whether two groups differ enough to be significant. The null hypothesis is that the groups are similar, the alternative hypothesis is that the groups differ a significant amount. z-test and p-value was calculated for question and parameter combinations. Since it requires exactly two groups, the dataset was split into those who answered with A and those who did not answer with A. Most differentiating motion parameter per question with p-value of any of the answers below 0.05 are listed here.

Table 3.2: z-test results for "Built with hands" and "velocity mass, relative index tip Y, test 2, cycle 2".

Answer	z-test	p-value
1 - not at all	-1.234986599	0.216835492
2 - rarely	0.332523791	0.739493778
3 - sometimes	-0.911050842	0.362268586
4 - often	-4.747868893	2.06E-06
5 - very often	1.70272935	0.08861873

Table 3.3: z-test results for "Learning style" and "trajectory mass, relative index tip X, test 8, cycle 5".

Answer	z-test	p-value
Auditiivne	-2.329238885	0.019846414
Auditiivne, Kinesteetiline	-3.783514456	0.000154629
Auditiivne, Visuaalne	-1.035508917	0.300431304
Kinesteetiline	-0.994512047	0.319973643
Visuaalne	0.720450163	0.471247874
Visuaalne, Kinesteetiline	1.172204231	0.24111507

Table 3.4: z-test results for “Solving logical” and “acceleration / time, index tip Z, test 3, cycle 2”.

Answer	z-test	p-value
1 - not at all	-0.510491392	0.609707244
2 - rarely	0.774275848	0.438767683
3 - sometimes	-3.482024354	0.000497638
4 - often	-0.791537368	0.428630479
5 - very often	1.933141638	0.053218752

Table 3.5: z-test results for “Tired/lively” and “acceleration / time, _relative index tip Y, test 2, cycle 4”.

Answer	z-test	p-value
1 - not at all	1.917043496	0.055232406
2 - rarely	-0.124310269	0.901069617
3 - sometimes	-2.698708121	0.00696092
4 - often	-2.013933762	0.044016488
5 - very often	0.634675658	0.525639973

Table 3.6: z-test results for “Phone communication” and “trajectory mass, relative index tip Z, test 9, cycle 1”.

Answer	z-test	p-value
2 - rarely	2.471718374	0.01344654
3 - sometimes	-2.317105147	0.020498005
4 - often	-0.479673744	0.631459401
5 - very often	-0.670802533	0.502346334

Table 3.7: z-test results for “Sports” and “velocity mass, index tip X, test 2, cycle 2”.

Answer	z-test	p-value
1 - not at all	2.319185495	0.020384981
2 - rarely	-0.33270992	0.739353261
3 - sometimes	-1.069734675	0.284738754
4 - often	-0.834953246	0.403744033
5 - very often	-2.046513461	0.040705879

Table 3.8: z-test results for “Studying goes well” and “acceleration / time, index tip Y, test 4, cycle 1”.

Answer	z-test	p-value
1 - not at all	0.030800073	0.975428982
2 - rarely	1.944829468	0.051795506
3 - sometimes	-0.984339823	0.324948455
4 - often	-0.829953588	0.406565025
5 - very often	-1.065282353	0.286748176

The p-value of this last combination was not below 0.05, but 0.065 is very close.

Table 3.9: z-test results for “Learning is easy” and “acceleration / time, wrist X, test 2, cycle 3”.

Answer	z-test	p-value
1 - not at all	1.065406475	0.286692028
2 - rarely	0.427187845	0.669242514
3 - sometimes	0.276921292	0.781840543
4 - often	-1.677657969	0.093413889
5 - very often	-1.845740308	0.064929921

3.3 Fisher score

Fisher score describes suitability of the variable to be used as classifier input. Roughly speaking, Fisher score describes discriminative power of the feature wih respect to the given label set.

To identify the best question and motion parameter combinations, Fisher score was calculated for each. Fisher score treats the answers as labels, which means that they don't need to have any numeric value or any meaningful order.

Only learning styles and "built with hands" had 21 and 9 values above 0.3, respectively. Three best for each are visualised on table 3.10. Other three questions had only one motion parameter each (table 3.11).

Table 3.10: The two questions with several good Fisher scores.

Parameter	Fisher score
Learning styles	
velocity mass, relative index tip Z, test 8, cycle 5	0.503611631
acceleration mass, relative index tip Z, test 8, cycle 5	0.491116417
jerk mass, relative index tip Z, test 8, cycle 5	0.475513949
Today I have already built something with my hands	
acceleration / time, relative index tip Z, test 1	0.398319917
distance, index tip X, test 11, cycle 3	0.38100199
velocity mass, relative index tip Z, test 2, cycle 2	0.355782419

Table 3.11: The other three questions with barely good enough Fisher score.

Parameter	Fisher score
Today I feel tired/lively	
acceleration / time, wrist Y, test 12, cycle 4	0.308789422
I use my smartphone for communication	
trajectory mass, wrist X, test 9, cycle 1	0.300891107
I solve logical problems (e.g. sudoku) in my spare time	
acceleration / time, wrist Z, test 8, cycle 5	0.298431333

3.4 Pearson correlation coefficient

Pearson coefficient describes the strength of linear relationship between two variables. Because of this, the learning style question could not be used.

"Separate" means that all answers were used directly, "joined" means that extremes were merged, i.e. 1 was equaled to 2 and 4 was equaled to 5.

As visible on the table 3.12, there were many weak correlations.

Table 3.12: Pearson correlation coefficients.

Parameter	data type	correlation
I feel that studying goes well		
trajectory mass, index tip X, test 9	separate	-0.3892349
trajectory mass, index tip Z, test 9	separate	-0.369076927
dtw, index tip X, test 11, cycle 3	joined	-0.362378308
Today I feel sad/happy		
distance, wrist Z, test 10, cycle 3	joined	0.350212772
distance, wrist Z, test 10, cycle 3	separate	0.31257681
I use the smartphone for playing		
trajectory mass, index tip X, test 5, cycle 1	joined	-0.33928096
trajectory mass, index tip X, test 5, cycle 1	separate	-0.319822501
trajectory mass, index tip Z, test 5, cycle 1	joined	-0.318028639
I use my smartphone for communication		
trajectory mass, relative index tip X, test 9, cycle 1	joined	-0.312353609
trajectory mass, wrist X, test 9, cycle 1	joined	-0.30515031
trajectory mass, wrist Y, test 9, cycle 1	joined	-0.30429514

3.5 Decision trees

Decision trees classify by taking several features into account. Boosting is used to build a strong learner out of weak ones. The methods differ in how the trees are trained and put together.

These methods were trained with best fields according to Fisher scores. All results were cross-validated with K-fold, the accuracy and standard deviation (stability) of each group is displayed.

Decision trees identified three questions that can be predicted (table 3.13).

Table 3.13: Decision trees.

Question	Nr of used params	Accuracy	Standard deviation of cross-validation score
Built with hands	6	0.754274264	0.051301273
	10	0.753722003	0.073255089
	5	0.753035793	0.062346684
	7	0.744045894	0.114429119
	13	0.726369126	0.059669895
Studying goes well	5	0.620416118	0.120562974
	9	0.618467282	0.085808308
	11	0.613114844	0.105068351
	8	0.608723101	0.086905479
	6	0.607433026	0.136848679
Sad/happy	3	0.638147782	0.042464835
	9	0.614816645	0.053493405

AdaBoost identified 5 more questions and improved the accuracy and stability (standard deviation) of the existing ones. The questions are listed on table 3.14.

Since learning styles sometimes had several answers per participant, different combinations of grouping and exclusion were tried. "Learning styles without mixed options" stood out with AdaBoost and it means that when the learning style of a participant had several answers, for example "Auditory, Visual", it was excluded.

Table 3.14: AdaBoost results.

Question	N estimators	Accuracy	Standard deviation of cross-validation score
Built with hands	10	0.813288318	0.039459214
Smartphone for communication	60	0.701086957	0.067617988
Solving logical	90	0.679265481	0.063341653
Dancing	3	0.644578549	0.056734018
Studying goes well	50	0.672787659	0.052567321
Sad/happy	3	0.639163373	0.104101258
Learning is easy	7	0.556982872	0.10884776
Learning styles without mixed options	65	0.533138402	0.097564424

As seen on table 3.15, **gradient boosting** identified two new questions:

- "Today I have already done something on my smartphone that needs finger dexterity (games, typing)"
- "It is easy for me to wake up in the morning"

Table 3.15: Gradient boosting results.

Question	N estimators	Accuracy	Standard deviation of cross-validation score
Built with hands	5	0.761496487	0.024189633
Studying goes well	80	0.719779315	0.082400056
Sad/happy	5	0.666254941	0.041326868
Phone communication	7	0.655906895	0.074848633
Dancing	20	0.640943597	0.060002126
Dexterity used	10	0.615393061	0.070560727

All four that **support vector machine** (SVM) identified, it classified better than the other boosters (table 3.16).

Table 3.16: Support vector machine results.

Question	Accuracy	Standard deviation of cross-validation score
Built with hands	0.841721563	0.024139413
Learning is easy	0.715689504	0.012330411
Sad/happy	0.696530523	0.024750115
Dancing	0.672297509	0.021318941

Each boosting method improved the score and stability of a few questions. Best method of each question is shown in table 3.17.

Table 3.17: Best method per question.

Question	It is easy for me to learn	N	Accuracy	Standard deviation of cross-validation score
Built with hands	SVM	-	0.841721563	0.024139413
Studying goes well	Gradient	80	0.719779315	0.082400056
Learning is easy	SVM	-	0.715689504	0.012330411
Smartphone for communication	AdaBoost	60	0.701086957	0.067617988
Sad/happy	SVM	-	0.696530523	0.024750115
Solving logical	AdaBoost	90	0.679265481	0.063341653
Dancing	SVM	-	0.672297509	0.021318941
Dexterity used	Gradient	10	0.615393061	0.070560727
Easy morning wakeup	Gradient	50	0.584121494	0.108515691
Drawing	Gradient	20	0.548105276	0.12085344
Learning styles without mixed options	AdaBoost	65	0.533138402	0.097564424

4 Discussion

Out of the 19 questions asked, 11 of them showed weak to moderate correlation with motor functions. The rest did not appear to be related, a different set of tests or more accurate equipment might be necessary.

The learning styles question was on the limit of almost any correlation and the techniques might need some adjustment and extra research to get any definite correlations. On the other hand, this styles model has been called pseudoscience and myth and there might not be any correlation to find at all.

Since there are many different models of learning styles, it might be a good idea select one that has had more scientific background.

Learning styles test is a third-party application with unknown implementation how the results are calculated. It also sometimes gave results with multiple styles, not specifying the proportions. The test did not require answering to all questions either.

One child had a lot of trouble understanding and answering to the phrases so the author tried to explain and rephrase them. Since everyone in a class filled the questionnaires at once, some more children might have had problems with the questions.

The tests were carried out during class, which meant that the participants had a lot of possible distractions: the teacher sometimes answered questions, reminded about the current task, or another child communicated with the one drawing at the moment. There were several participants at once and they sometimes had short conversations, commenting about test progress or difficulty. Keeping the testing distraction-free might give different results.

Some participants did not take the tests seriously and would just doodle on the test area or get bored and trace a very general representation of the pattern. These outliers might need extra segmentation for certain sensitive analysis methods.

Drawing in air with index finger left a lot of options how to hold the hand. Sometimes an elbow was rested on the table, sometimes the other hand was used to support the first one. Since 12 tests took several minutes in total, the participant's hand would surely get tired at some point. As which hand to use was not specified, some children would switch hands between tests.

For this thesis, same Luria tests were used as in the pencil draw thesis [4]. Other tests might have had better success.

The "continue" test was sometimes not understood since the participant traced the single guiding pattern and then immediately ended the test.

With each frame, LM included a confidence parameter, showing how well it estimates the model to match with the captured stereo image. Confidence of frames varied a lot. It is said that external light conditions affect tracking accuracy and frame rate, yet the diagnostic tool reported that lighting is fine. The lighting conditions were similar the whole time. A more accurate tracking might be needed for better results. An alternative to try could be moving the display to virtual reality headset and darken the whole test area since then the LM wouldn't have any external disruptors, including the computer screen.

Another issue of the Leap Motion controller was decreased tracking capabilities on the edges of its vision. As each test required drawing a pattern four times from left to right, the start and end of the test had to be close to the edge. With a lower model confidence, the cursor would sometimes become jumpier and cause difficulty with drawing. Keeping a hand strictly in line with the controller slightly improves tracking. While demonstrating the program to the children, the author highlighted that issue and the alleviation. Nevertheless, the hand of some children tended to drift toward or away from the computer and the author needed to remind them about it. One future improvement to the program could be visualising the depth as a constant reminder to keep the hand above the controller.

This issue could be solved with virtual reality as well, since the participant could keep drawing the patterns while keeping the hand right in the optimal area.

5 Conclusion

This thesis successfully showed that Luria alternating series tests and motion mass can be used to assess certain moods, habits, hobbies, success at school and activities of the day.

In addition, Leap Motion has proven to be a device with sufficient accuracy for fine motor analysis.

As a side goal, the program developed can be well used to carry out such drawing tests. In the future, more test types can be added to the software as needed. Another improvement could be immediate responses based on the achieved analysis results.

All the extra data gathered but not used as part of this thesis could be analysed in future research.

Bibliography

[1] Sven Nõmm, Tiit Kõnnusaar, and Aaro Toomela. "Towards Establishing Relationships between Human Arousal Level and Motion Mass". In: *Lecture Notes in Computer Science*. 2014, pp. 19–26.

[2] Sven Nõmm and Aaro Toomela. "An alternative approach to measure quantity and smoothness of the human limb motions". In: *Estonian Journal of Engineering* 19.4 (2013), pp. 298–308.

[3] Sven Nõmm, Aaro Toomela, and Jevgeni Boruško. "Alternative Approach to Model Changes of Human Motor Functions". MA thesis. Tallinn University of Technology, 2014.

[4] Julia Koženkina. "Quantitative Analysis of the kinematic features for the Luria's alternating series test". MA thesis. Tallinn University of Technology, 2016.

[5] S. Nõmm et al. "Recognition and Analysis of the Contours Drawn during the Poppelreuter's Test". In: *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*. Dec. 2016, pp. 170–175. DOI: 10.1109/ICMLA.2016.0036.

[6] Ilja Mašarov. "Digital clock drawing test implementation and analysis". MA thesis. Tallinn University of Technology, 2017.

[7] M. Wang et al. "Quantitative evaluation of hand movement in spiral drawing for patients with Parkinson's disease based on modeling in polar coordinate system with varied origin". In: *The 2011 IEEE/ICME International Conference on Complex Medical Engineering*. May 2011, pp. 169–173. DOI: 10.1109/ICCME.2011.5876726.

[8] Jaroslav Kulikov. "Virtual reality aided framework for modeling changes in finger motion and orientation during learning fine motor activity". MA thesis. Tallinn University of Technology, 2017.

[9] Frank Weich et al. "Analysis of the Accuracy and Robustness of the Leap Motion Controller". In: *Sensors* 13.5 (May 2013), pp. 6380–6393.

[10] M. A. Seif, R. Umeda, and H. Higa. "An attempt to control a 3D object in medical training system using leap motion". In: *2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*. Nov. 2017, pp. 159–162. DOI: 10.1109/ICIIBMS.2017.8279705.

[11] T. Wright, S. de Ribaupierre, and R. Eagleson. "Design and evaluation of an augmented reality simulator using leap motion". In: *Healthcare Technology Letters* 4.5 (2017), pp. 210–215. DOI: 10.1049/htl.2017.0070.

[12] A. H. Butt et al. "Leap motion evaluation for assessment of upper limb motor skills in Parkinson's disease". In: *2017 International Conference on Rehabilitation Robotics (ICORR)*. July 2017, pp. 116–121. DOI: 10.1109/ICORR.2017.8009232.

[13] R. L. Trejo et al. "Hand goniometric measurements using leap motion". In: *2017 14th IEEE Annual Consumer Communications Networking Conference (CCNC)*. Jan. 2017, pp. 137–141. DOI: 10.1109/CCNC.2017.7983095.

[14] W. J. Li et al. "Hand gesture recognition for post-stroke rehabilitation using leap motion". In: *2017 International Conference on Applied System Innovation (ICASI)*. May 2017, pp. 386–388. DOI: 10.1109/ICASI.2017.7988433.

[15] X. Wei et al. "A method of rehabilitation training for finger pair movement based on multi - Leap motions". In: *2017 2nd International Conference on Information Technology (INCIT)*. Nov. 2017, pp. 1–6. DOI: 10.1109/INCIT.2017.8257886.

[16] I. M. Moldovan et al. "Virtual rehabilitation programme using the MIRA platform, Kinect and Leap Motion sensors in an 81 years old patient with ischemic stroke". In: *2017 E-Health and Bioengineering Conference (EHB)*. June 2017, pp. 325–328. DOI: 10.1109/EHB.2017.7995427.

[17] Y. Ji et al. “3D Hand Gesture Coding for Sign Language Learning”. In: *2016 International Conference on Virtual Reality and Visualization (ICVRV)*. Sept. 2016, pp. 407–410. DOI: 10.1109/ICVRV.2016.74.

[18] A. Eqab and T. Shanableh. “Android mobile app for real-time bilateral Arabic sign language translation using leap motion controller”. In: *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*. Nov. 2017, pp. 1–5. DOI: 10.1109/ICECTA.2017.8251936.

[19] M. D. Wibowo, I. Nurtanio, and A. A. Ilham. “Indonesian sign language recognition using leap motion controller”. In: *2017 11th International Conference on Information Communication Technology and System (ICTS)*. Oct. 2017, pp. 67–72. DOI: 10.1109/ICTS.2017.8265648.

[20] Khamid, A. D. Wibawa, and S. Sumpeno. “Gesture Recognition for Indonesian Sign Language Systems (ISLS) Using Multimodal Sensor Leap Motion and Myo Armband Controllers Based-on Naive Bayes Classifier”. In: *2017 International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT)*. Sept. 2017, pp. 1–6. DOI: 10.1109/ICSIIT.2017.42.

[21] P. Kumar et al. “Real-time recognition of sign language gestures and air-writing using leap motion”. In: *2017 Fifteenth IAPR International Conference on Machine Vision Applications (MVA)*. May 2017, pp. 157–160. DOI: 10.23919/MVA.2017.7986825.

[22] M. Ataş. “Hand Tremor Based Biometric Recognition Using Leap Motion Device”. In: *IEEE Access* 5 (2017), pp. 23320–23326. DOI: 10.1109/ACCESS.2017.2764471.

[23] K. Komiya and T. Nakajima. “A Japanese input method using leap motion in virtual reality”. In: *2017 Tenth International Conference on Mobile Computing and Ubiquitous Network (ICMU)*. Oct. 2017, pp. 1–2. DOI: 10.23919/ICMU.2017.8330085.

[24] Q. Wang et al. “Hand gesture recognition of Arabic numbers using leap motion via deterministic learning”. In: *2017 36th Chinese Control Conference (CCC)*. July 2017, pp. 10823–10828. DOI: 10.23919/ChiCC.2017.8029083.

[25] C. Chen et al. "Controlling a robot using leap motion". In: *2017 2nd International Conference on Robotics and Automation Engineering (ICRAE)*. Dec. 2017, pp. 48–51. DOI: 10.1109/ICRAE.2017.8291351.

[26] L. L. Cheng and H. B. Liu. "Examples of quadrocopter control on ROS". In: *2015 IEEE 9th International Conference on Anti-counterfeiting, Security, and Identification (ASID)*. Sept. 2015, pp. 92–96. DOI: 10.1109/ICASID.2015.7405668.

[27] Y. T. Cheng, T. K. Shih, and C. Y. Lin. "Create a puppet play and interative digital models with leap Motion". In: *2017 10th International Conference on Ubi-media Computing and Workshops (Ubi-Media)*. Aug. 2017, pp. 1–6. DOI: 10.1109/UMEDIA.2017.8074081.

[28] Mihhail Lapuškin. "Application for Control of the "Pioneer" Robot with Manipulator". Tallinn University of Technology, 2009.

[29] Mihhail Lapuškin. "Application for Gesture Based Control of the "Pioneer" Robot with Manipulator". MA thesis. Tallinn University of Technology, 2012.

[30] Kenno Parm. "Scrub Nurse Robot voting automata for detecting and learning motions". MA thesis. Tallinn University of Technology, 2010.

[31] Siim Kirme. "Recognition of Hand Gestures Using Bezier Curve and K-nearest Neighbors Method". Tallinn University of Technology, 2016.

[32] Samet Erap. "Gesture Based PC Interface with Kinect Sensor". MA thesis. Tallinn University of Technology, 2012.

[33] Kirill Buhhalko. "Monitoring of the human motor functions rehabilitation by neural networks based system with Kinect sensor". MA thesis. Tallinn University of Technology, 2013.

[34] Helena Lissenko. "Multi-Kinect system for acquisition of turning motion". MA thesis. Tallinn University of Technology, 2015.

[35] Ahmed Abdelhady. "Low cost gait capture during turning motion". MA thesis. Tallinn University of Technology, 2017.

[36] Kris-Gerhard Aabrams. "Correctness Analysis of Captured Skeleton Model". Tallinn University of Technology, 2017.

[37] Jan-Joonas Bernstein. “Context Based Registration and Analysis of Human Motions”. Tallinn University of Technology, 2017.

[38] Maria Kohtla. “Gesture evaluation for Leap Motion”. MA thesis. Tallinn University of Technology, 2015.

[39] Alexander Romanovich Luria. *Higher Cortical Functions in Man*. Springer, 1995.

[40] Alex Colgan. *How Does the Leap Motion Controller Work?* URL: `http://blog.leapmotion.com/hardware-to-software-how-does-the-leap-motion-controller-work/` (visited on).

[41] *Leap Motion JavaScript SDK v3.2 Beta documentation*. URL: `https://developer.leapmotion.com/documentation/javascript/devguide/Leap_Overview.html`.

[42] *Õpistiili määramise test*. URL: `https://www.syg.edu.ee/~peil/opi_oppima/stiili_test.html`.

[43] F. Pedregosa et al. “Scikit-learn: Machine Learning in Python”. In: *Journal of Machine Learning Research* 12 (2011), pp. 2825–2830.

[44] URL: `https://github.com/pierre-rouanet/dtw`.

Appendix A – Original learning styles questions

Mulle jäävad uued asjad paremini meelde pigem neist kellegagi rääkides kui nende kohta raamatust lugedes.

Ma eelistan uut infot saada plakatite, raamatute ja / või video kaudu.

Mulle jääb uus materjal paremini meelde siis, kui selle kuhugi üles kirjutan. Seejuures joonin konspektis (vahel ka raamatutes) tähtsad kohad alla.

Ma omandan uut materjali kergemini siis, kui valmistan ise teemakohase mudeli, plakati või mõne muu loomingulise töö.

Uute ülesannetega saan kõige kiiremini hakkama just siis, kui keegi mulle kõrval rääkides selgitab, mida tegema pean.

Uus asi jääb kõige paremini meelde siis, kui saan oma kätega midagi teemaga seout valmis teha.

Uut osa selgitava õpetaja vaatamine aitab mul materjali omandamisele keskenduda.

Kui pean kellelegi rääkima, kuidas midagi teha tuleb, saan selgitustega kenasti hakkama.

Õpetaja selgitusi kuulates sirgeldan ise seda vahel märkamatagi paberile mitmesuguseid kujundeid või pildikesi.

Kui õpetaja seletab uut keerulist osa, siis tahaksin, et ta kasutaks rääkimise kõrval rohkem tahvlit, stende või grafoprojektorit.

Mulle meeldib õppimise ajal valjusti lugeda.

Eriti hästi jäävad asjad mulle meelde siis, kui need mitu korda läbi kirjutan.

Mu konspektid ja töövihikud on üsna korratu väljanägemisega.

Eelistan õppimise ajal üksi olla.

Mulle meeldib õppimise ajal midagi näksida / süüa.

Kontrolltööd kirjutades näen mõttes oma konspekti või õpikut.

Õppimise ajal teen sagedasi puhkepause.

Uue materjali lugemisele eelistaksin seda kellegi suust kuulata (sõber, õpetaja, helisalvestis...).

Lahendan hästi geomeetrilisi nuputusülesandeid (labürindid, pusled, piltmõistatused...)
Kodutööde tegemise ajal ma nihelen või mängitan midagi näppude vahel (pastakas, kustutuskumm, kommipaber...).

Olen lugemise ajal hajevil ning ümbritsev tõmbab tähelepanu raamatult eemale.

Mulle meeldib uute asjade kohta raamatutest või Internetist lugeda.

Mulle meeldib sportida ja olen mõnel alal isegi päris tugev.

Materjali kordamisel jutustan õpitu valjult endale või sõbrale ette.

Kui annan kellelegi juhtnööre, teen seda väga üksikasjaliselt.

Ülesandeid lahendades meeldib mulle jooniseid või diagramme kasutada ja neid ka ise teha.

Kui annan kellelegi juhtnööre, siis püüan seda teha võimalikult konkreetselt ja napisõnaliselt.

Kui keegi mulle midagi selgitab, siis kuulan teda hea meelega ja räägin ise vahele ka.

Kui pean meelde jätma mingite esemete välimust või omadusi, eelistan neid enda kätte võtta, laual ümber paigutada või niisama katsuda.

Lahendades mõnda keerukamat ülesannet aitab ringiliikumine või esemete ümberpaigutamine mul mõtteid koondada.

Appendix B – Original questionnaire questions

Ma mängin vabal ajal arvuti- või konsoolimänge

Ma teen vabal ajal sporti

Ma käin vabal ajal tantsimas

Kasutan nutitelefoni suhtlemiseks

Kasutan nutitelefoni mängimiseks

Lahendan vabal ajal loogilisi ülesandeid (nt sudoku)

Suhtlen sõpradega inglise keeles

Ma sirgeldan/joonistan

Ma laulan omaette

Jõuan matemaatika tunnis kõik ülesanded ära teha

Ma tunnen, et mul läheb õppimine hästi

Ma tunnen, et mul on lihtne õppida (tunnis osaleda, ülesandeid lahendada, koduseid töid teha)

Mul on hommikuti lihtne ärgata

Olen täna juba nutitelefonis teinud midagi sellist, mis sõrmeosavust vajab (mängud, kirjutamine)

Olen täna juba paberile kirjutanud

Täna on koolis juba vaja olnud midagi käelist teha (ehitada, valmistada)

Ma tunnen ennast täna (1 - kurvalt, 5 - rõõmsalt)

Ma tunnen ennast täna (1 - väsinult, 5 - erksalt)

Eile õhtul jäin magama umbes <aeg>

Appendix C - Distribution of answers

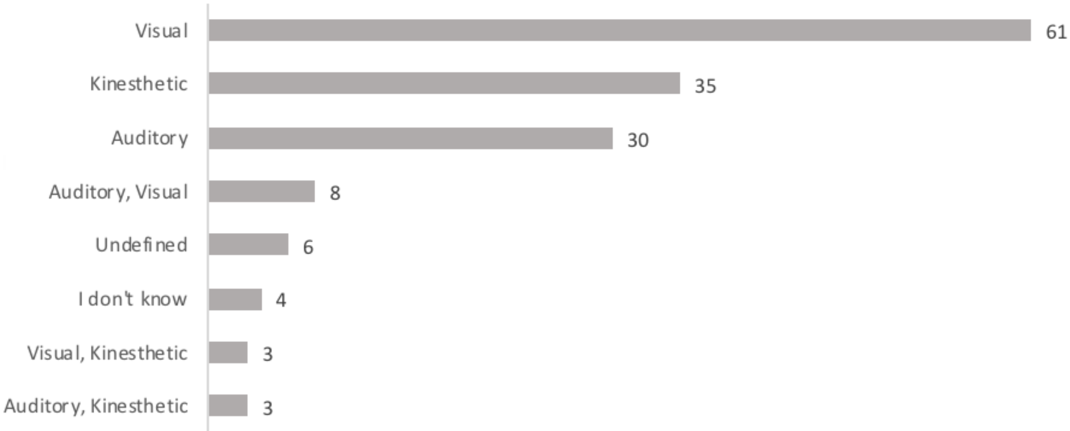


Figure 5.1: My result of the styles test.

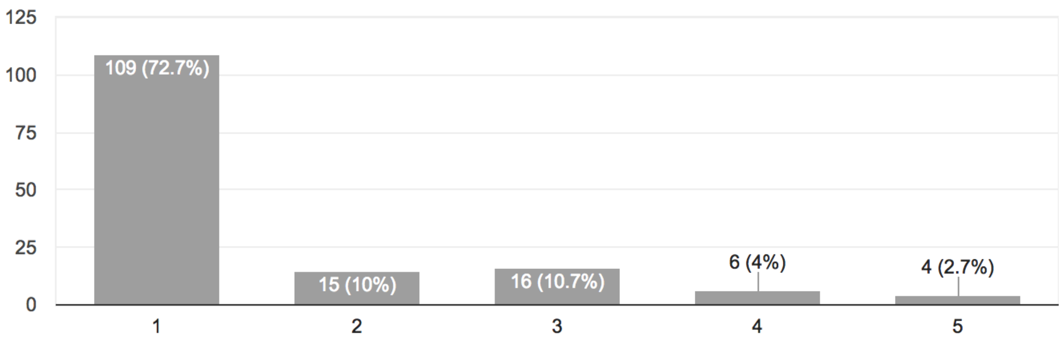


Figure 5.2: Today I have already done/built something with my hands.

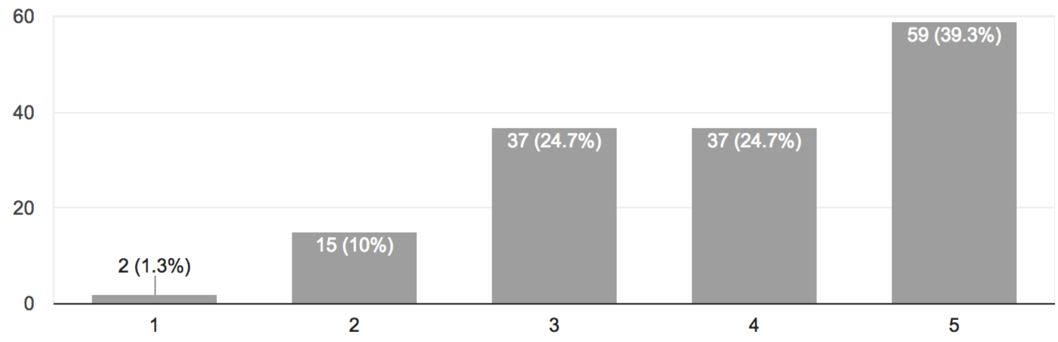


Figure 5.3: I use the smartphone for communication.

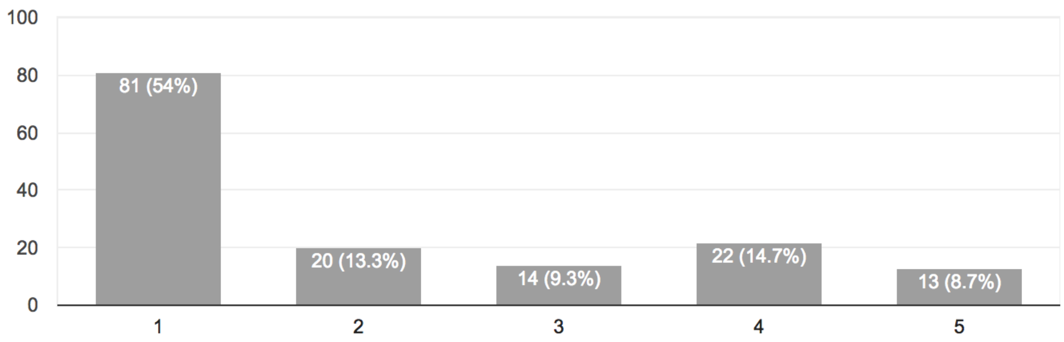


Figure 5.4: I dance in my spare time.

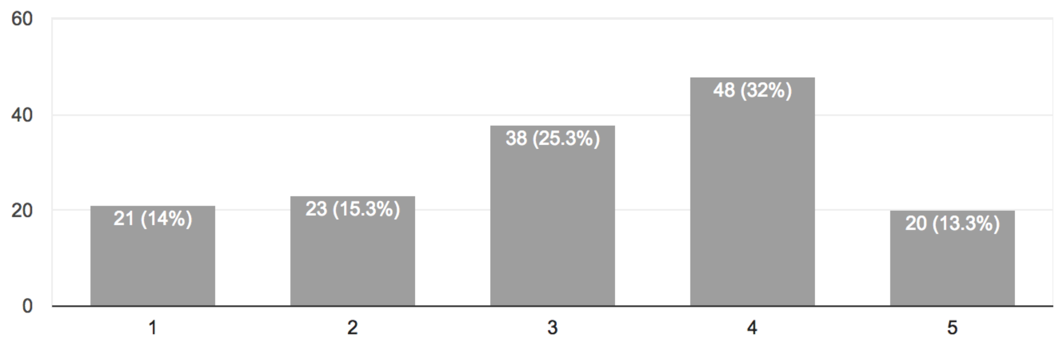


Figure 5.5: Today I have already done something on my smartphone that needs finger dexterity (games, typing).

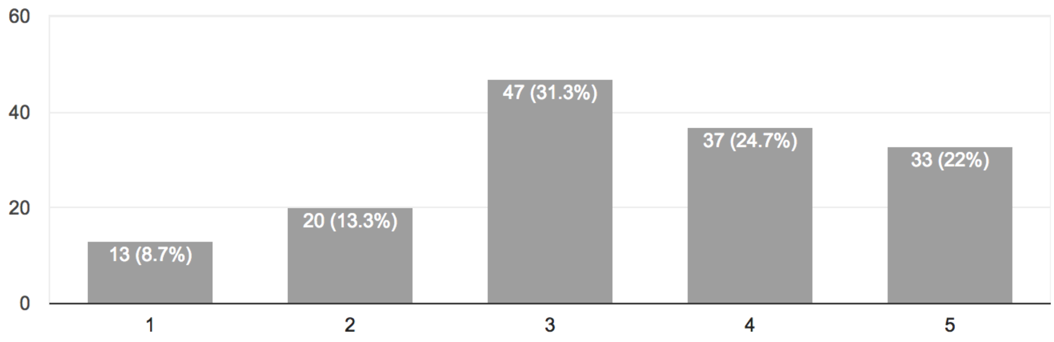


Figure 5.6: I draw/doodle.

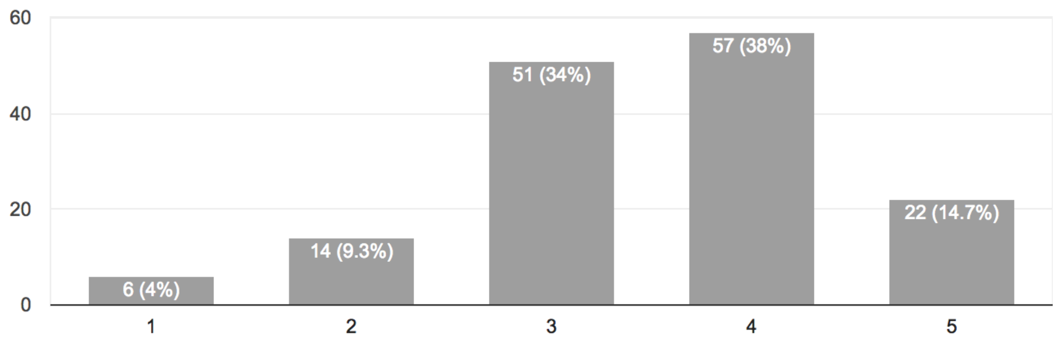


Figure 5.7: I feel that it is easy for me to learn (take part in class, complete tasks, do homework).

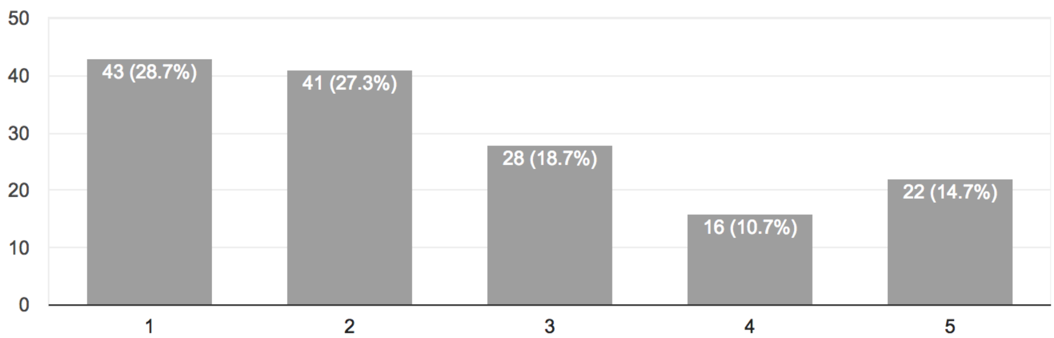


Figure 5.8: I talk to my friends in English.

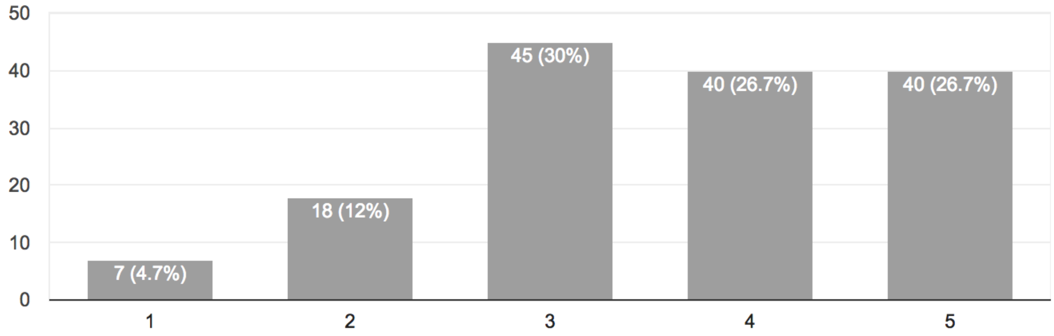


Figure 5.9: I can complete all the exercises during the mathematics class.

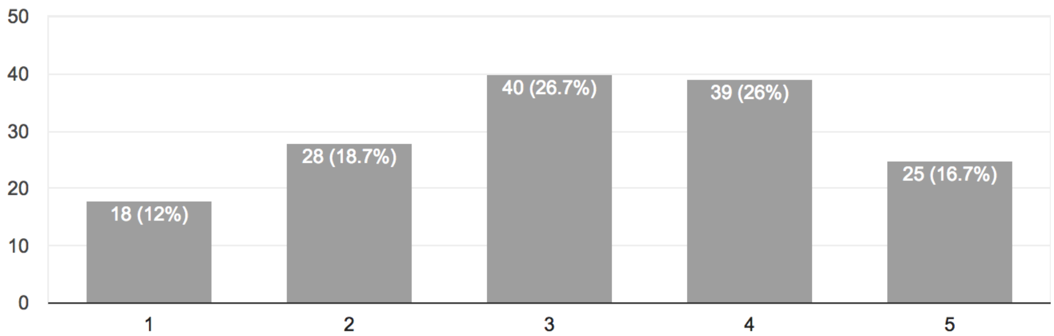


Figure 5.10: I play computer or console games in my spare time.

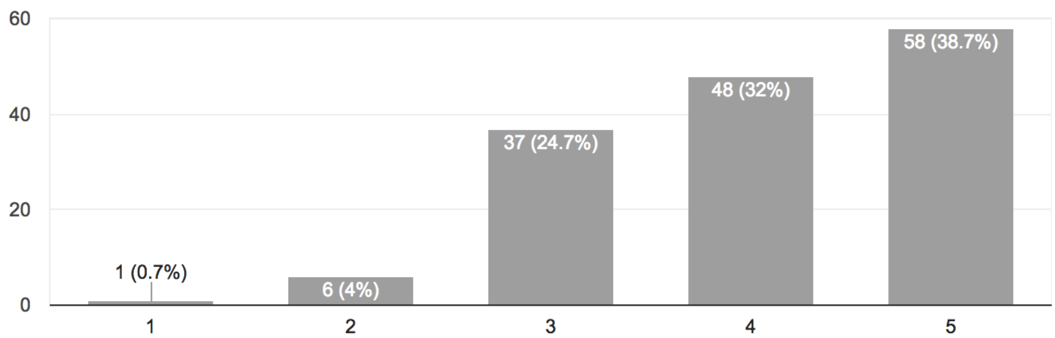


Figure 5.11: Today I feel sad/happy (in the scale of 1 to 5, sad is 1 and happy is 5).

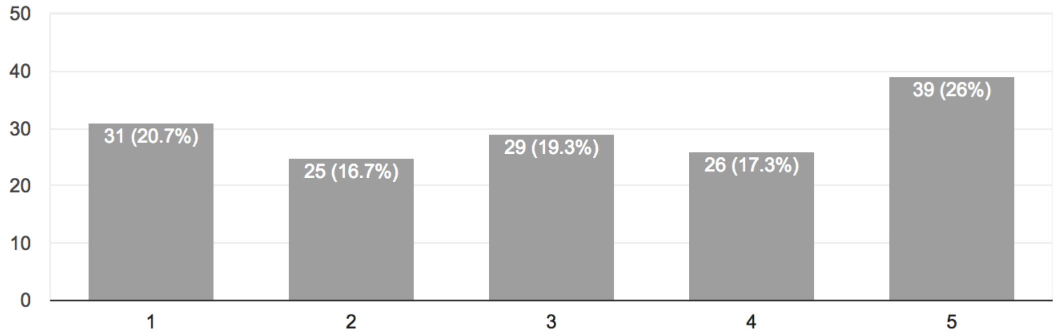


Figure 5.12: I sing on my own.

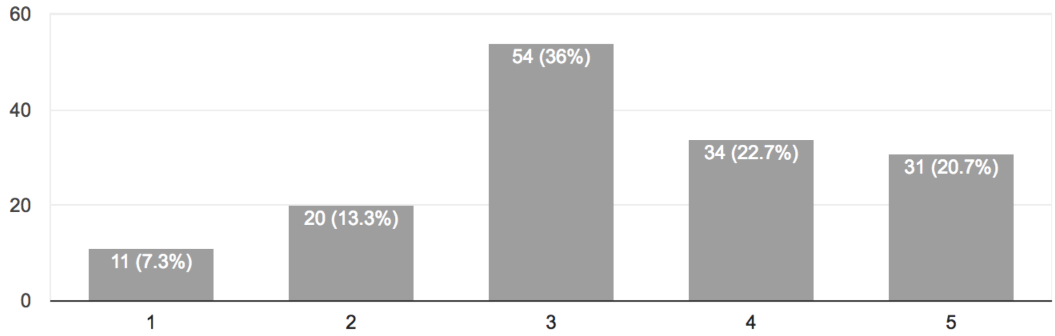


Figure 5.13: I use the smartphone for playing.

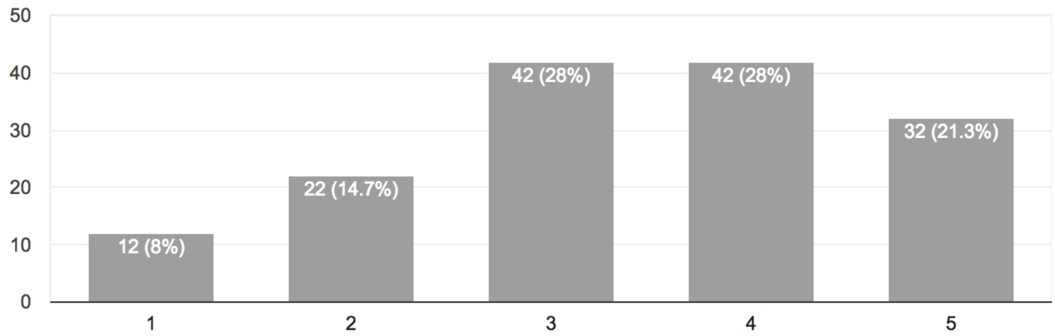


Figure 5.14: I do sports in my spare time.

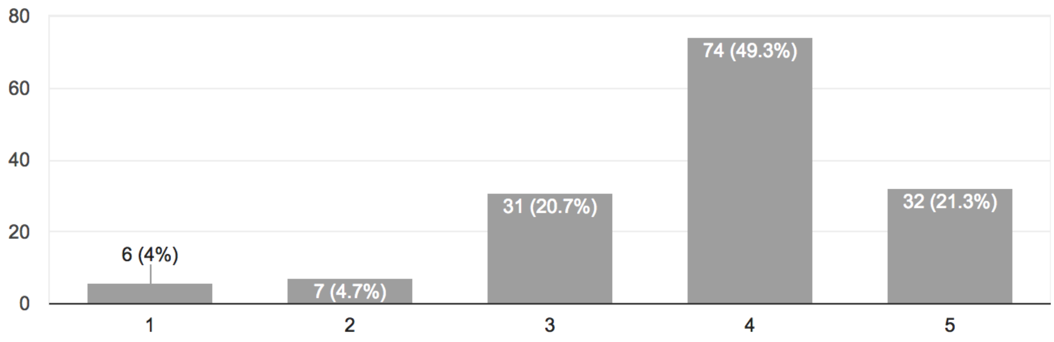


Figure 5.15: I feel that studying goes well.

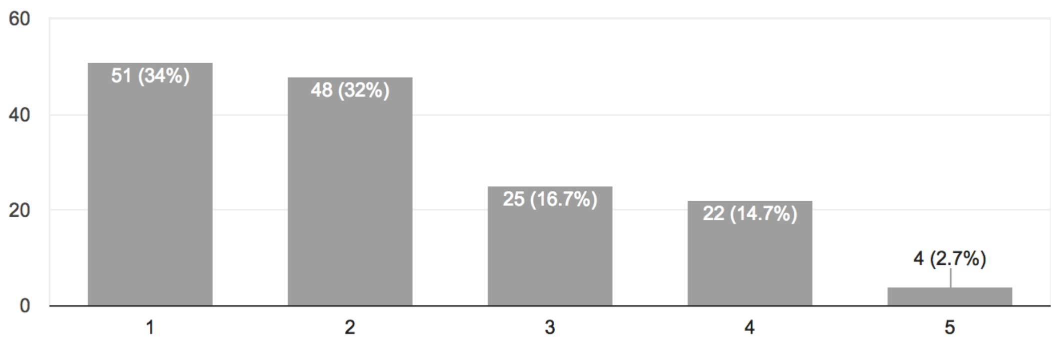


Figure 5.16: I solve logical problems (e.g. sudoku) in my spare time.

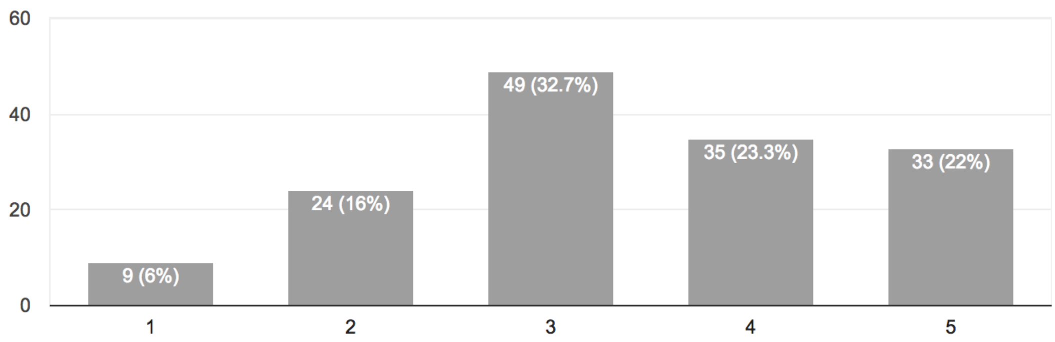


Figure 5.17: Today I feel tired/lively (in the scale of 1 to 5, tired is 1 and lively is 5).

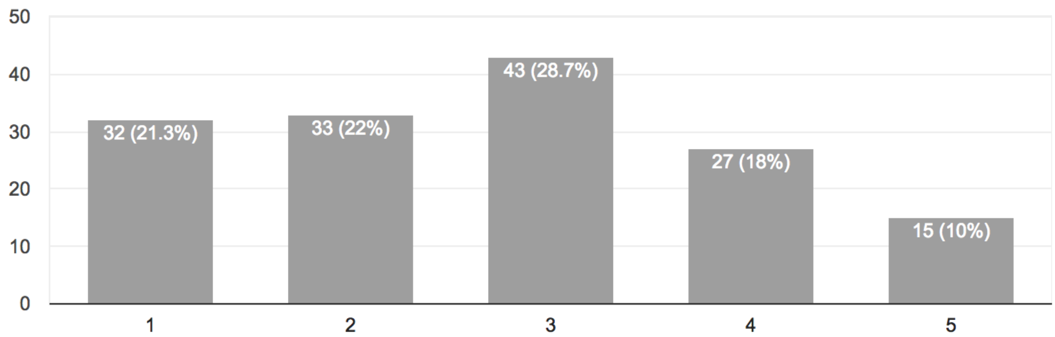


Figure 5.18: It is easy for me to wake up in the morning.

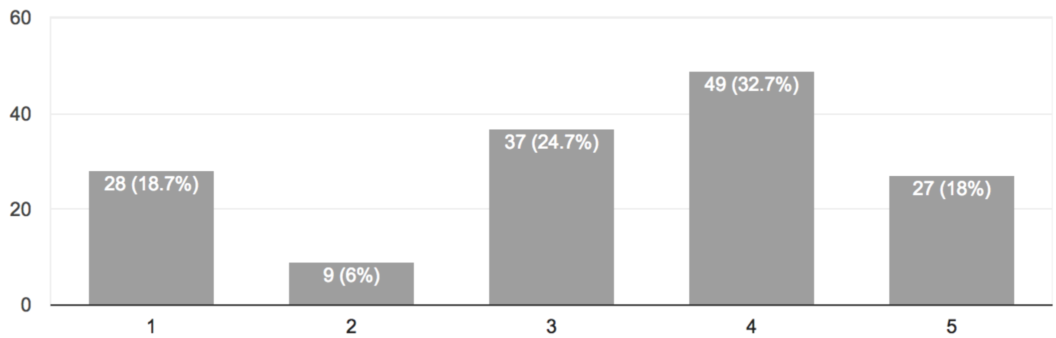


Figure 5.19: Today I have already written on paper.