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Performance Feedback for Cable Machine Strength Exercises Using Smartphone's Inertial Data

Master's thesis (15 EAP)

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Performance feedback for cable machine strength exercises using smartphone's inertial data

Abstract:

For the purpose of endurance training, devices have been produced for many years that allow measuring pace, heart rate, step length, distance covered, and thanks to this find the amount of spent energy and other performance parameters. For this, integrated inertial measurment units, or IMUs, are used. However, for strength training, such IMU-based solutions are not as common. For performance feedback, manual measurement of repetitions and used weights has to be done. Even then, motion is still not measured. To solve this, a method is proposed in this thesis to fetch useful exercise feedback metrics from acceleration data.

These metrics are:

- energy consumption in kilocalories
- repetition count
- peak power in Newtons.

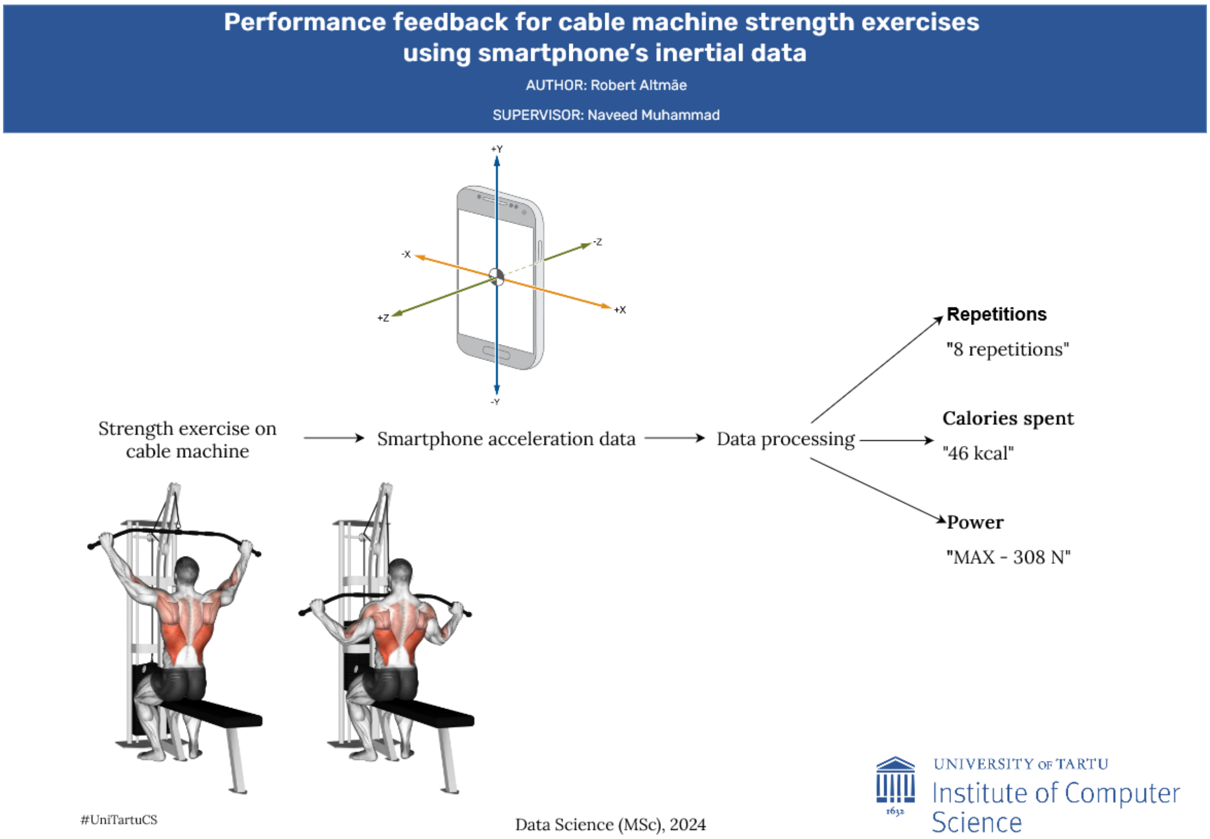
This work describes how the movement of a cable machine's weight stack in one axis was measured with an acceleration sensor of a mobile phone, and how the data was processed and useful indicators were found for exercise feedback. An overview of the strength exercise performed for data collection was given, the data collection hardware and software were described, and the results were analyzed and visualized. A baseline comparison was done to compare the method's results with theoretical calculations, showing promising results. In addition, problem areas related to noise and measuring were pointed out and possible ideas for further development are proposed. As a secondary part of the thesis, a software solution was developed in the form of a user interface and a server, the technological choices and implementation of which are described. A link to the source code repository is also given. This research has the potential to be used in health applications on smartphones.

Keywords:

Data, IMU, acceleration, exercise, repetition, strength, energy, calorie, training, software

CERCS: T120 Systems engineering, computer technology

Visual abstract:



Plokkmasina jõuharjutuste tulemuslikkuse tagasiside nutitelefoni inertsiaalandmeid kasutades

Lühikokkuvõte:

Vastupidavustreeningu tarbeks on juba aastaid toodetud seadmeid, mis võimaldavad mõõta tempot, pulssi, sammu pikkust, läbitud distantsi ning tänu sellele leida kulutatud energiahulka ja teisi mõõdikuid, kasutades peamiselt seadmetesse integreeritud inertsiaalandureid ehk IMU-sid. Jõutreeningu puhul pole aga sellised IMU-põhised lahendused levinud. Treeningu mõõdikute tagasiside saamiseks tuleb korduste arv ja kasutatud raskused manuaalselt mõõta. Isegi siis ei mõõdeta liikuvate kehade kiirendust. Treeningu tagasisidestamiseks on selles lõputöös välja pakutud meetod kasulike mõõdikute leidmiseks kiirendusandmetest.

Käsitletavad mõõdikud on:

- energiakulu kilokalorites
- korduste arv
- rakendatud jõud njuutonites.

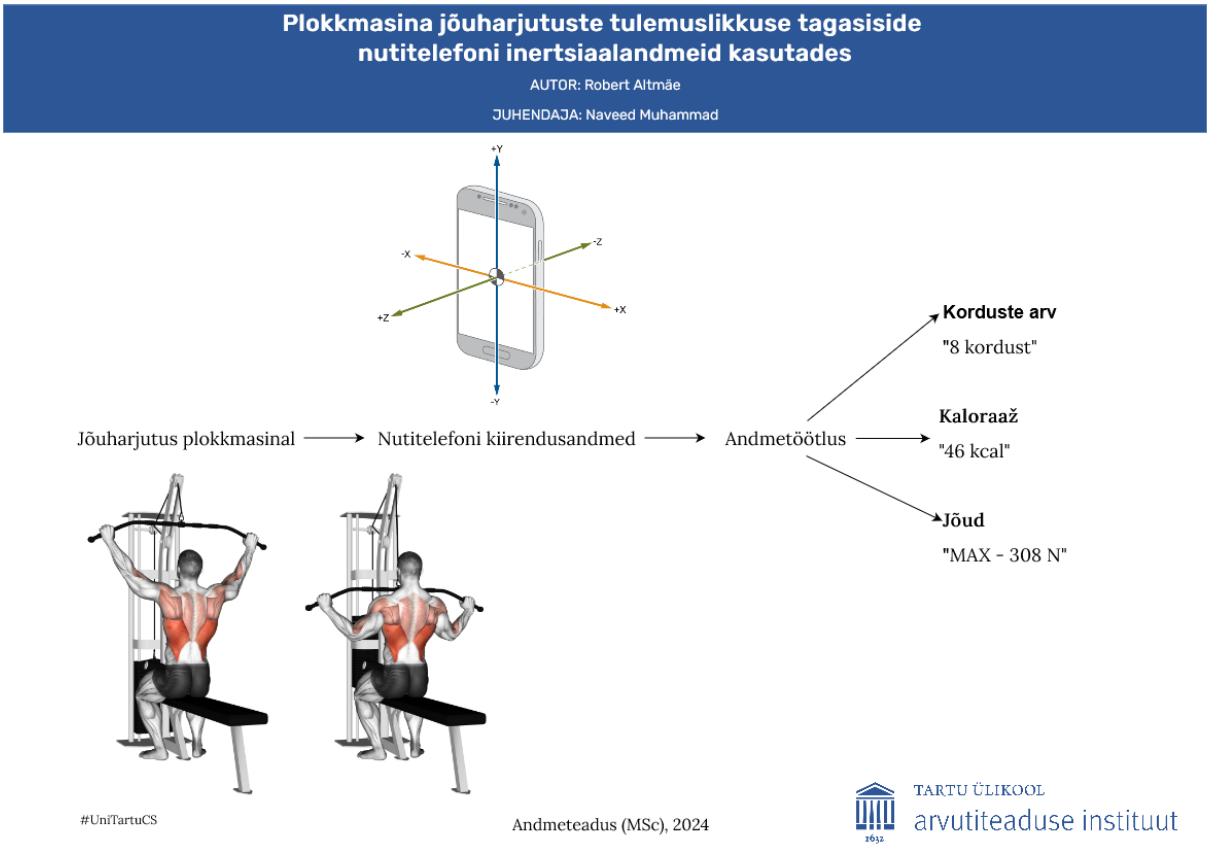
Käesolevas töös kirjeldatakse, kuidas mobiiltelefoni kiirendusanduriga mõõdeti plokkmasina raskuste liikumist ühel teljel ning kuidas toimus andmete töötlemine ja kasulike näitajate leidmine treeningu tagasisidestamiseks. Anti ülevaade andmete kogumiseks sooritatud jõuharjutusest, kirjeldati andmete kogumise riist- ja tarkvara ning analüüsiti tulemusi. Võrreldakse leitud tulemusi manuaalselt mõõdetud andmetega, näidates paljutõotavaid tulemusi. Lisaks tuuakse välja müra ja mõõtmisega seotud probleemkohad ning pakutakse välja võimalikke ideid tuleviku edasiarendusteks. Lõputöö teise eesmärgina töötati välja tarkvaralahendus kasutajaliidese ja serveri näol, mille tehnoloogilisi valikuid ja teostust kirjeldatakse. Samuti on antud link lähtekoodi hoidlale. Töö omab potentsiaali nutitelefoni terviserakendustes kasutuseks.

Võtmesõnad:

Andmed, IMU, kiirendus, harjutus, kordus, jõud, energia, kalor, treening, tarkvara

CERCS: T120 Süsteemitehnoloogia, arvutitehnoloogia

Visuaalne kokkuvõte:



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1. Introduction

The following chapter gives and overview of the context of the topic, focusing on strength training and how a cable machine and an Inertial Measurement Unit (IMU) sensor are relevant for the thesis. Various studies on similar topics are mentioned, and the arised problem is described. Finally, the structure of the manuscript is expanded.

1.1 Context

As this work aims to improve strength training by informative feedback, a short summary of strength training and a cable machine is given.

1.1.1 Strength Training

Strength training is a subtype of physical training, the purpose of which is to develop primarily strength and muscle endurance [1]. Such training is characterized by a repeated movement of weights at a high intensity anaerobically, thus loading and thereby stimulating muscle growth. Objects that are most commonly used as a load, are:

- a person’s bodyweight
- free weights
    - dumbbells
    - barbells
- dedicated machines.

In strength training, one of the most universal training machines is the cable machine [2], which allows a person to perform various exercises loading different muscle groups thanks to a cable moving on pulleys. At one end of the cable, there are metal weight plates and a perforated steel beam, through which the exerciser can choose the number of weight plates suitable for him and thus the training load. Different attachments can be installed on the other end of the cable to vary the exercises. Depending on the machine, the trainer can pull the cable from the top down or up from the bottom. In Figure 1, an exerciser performing a pulling exercise to train arm muscles is shown, with the exercise start position on the left and end position on the right. On some machines, the height of the pulley closest to the person can also be changed as desired.

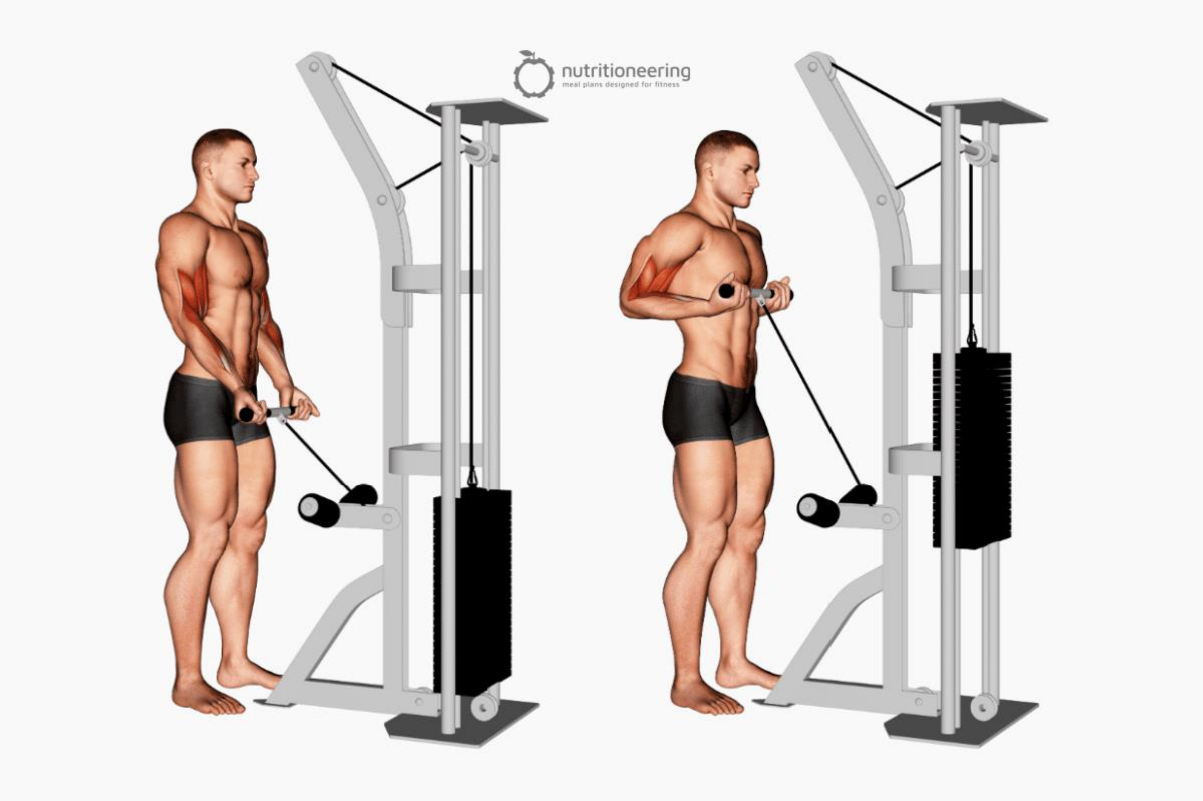


Figure 1. Bicep exercise on a cable machine [3].

1.1.2 Lat Pulldown

Of the many possible exercises that can be performed with a cable machine, one of the most popular ones is lat pulldown. It is an exercise with the main purpose of loading the *latissimus dorsi* muscles. The exercise is performed while sitting facing the weight plates, fixing the whole body with supports on top of the thighs. In the starting position of the movement, the training bar is up and the arms are stretched straight up. To bring it to the final position, the exerciser pulls the bar down to his chin. In addition to the *latissimus dorsi*, the exercise loads other back muscles, shoulder muscles, biceps and abdominal muscles. The final position of the exercise is shown in Figure 2, where a wide grip attachment is used, with *latissimus dorsi* in dark blue and other loaded muscles in light blue. Depending on the training bar's shape and grip width, it is possible to vary which muscles to load more [4].

Figure 2. Lat pulldown [5].

1.2 Problem

For endurance training purposes, feedback of performance metrics has been commonly available for use thanks to a high popularity of smartphones, smart watches, heart monitors and step counters. By counting steps, measuring acceleration and combining it with GPS data and logs from a heart monitor, a person's performance over time can be found. The most common such measurable endurance trainings are running, walking, hiking, cycling and swimming. In addition, counting steps taken across the entirety of the day can provide additional health benefits. The increase of wearable product popularity can be seen from Apple's increasing revenue from wearable sales [6] each quarter, where a steady increase over time is present in each quarter. In the first quarter of 2024 the sales of wearables generated $11.95 billion for Apple.

For measuring metrics from strength workouts, both step counting and GPS data are understandably uninformative. The steps taken during a strength exercise are most likely not correlated to the performance of a workout. In addition, the training environment is usually indoors under a roof, hindering GPS reception. Furthermore, location data of a workout is not useful since a strength workout's goals are achieved by moving of weights and use of specific machines, not by moving the person itself.

A strength exercise performed on a cable machine is a repeatable motion. To get feedback on workout performance, the exercising person has to remember the repetition count and the weights used for resistance per each performed exercise. In theory, it is then possible to analyze strength performance in workouts over time, gaining insights on muscle growth and benefits of different exercises.

As described then, for feedback over time, a person needs to measure:

- amount of repetitions
- mass of weights used.

On the other hand, there are more variables that can be measured. During a strength exercise on a cable machine, there are various objects in motion: the weight stack moves in a single axis against gravity; the handle in motion is in grip of the person; the person's body itself is in motion. Measuring motions on these bodies could prove useful to fetch more information out of the exercise performed, as well as enabling automatic count of repetitions.

This thesis explores how the single-axis motion of a cable machine's weight stack can be used for informative feedback on strength training.

1.3 Inertial Measurement Unit

The IMU sensor or Inertial Measurement Unit is a sensor that enables measuring of linear acceleration, angular velocity and tilt angle, by using acceleration sensors, gyroscopes and in some cases magnetic sensors. Thanks to developments in the electronics industry, components have shrunk over time in such a way that they can be installed in commonly used devices. IMU sensors are used, for example, in mobile phones, smart watches, aircraft, drones and autonomous vehicles [7]. Figure 3 shows an SBG Systems' AHRS (*Attitude and Heading Reference System*) device, which can output reliable position and heading information thanks to an EKF (*Extended Kalman Filter*) implemented using the built-in IMU and processor [8].

Figure 3. SBG Systems Ellipse-A [8].

IMUs have been used for feedback in fitness activities for some time. The first iPhone to implement an IMU to count steps, jogging performance and other motion parameters, was the iPhone 5s. The sensor consists of an accelerometer, MEMS gyroscope and a digital compass, tracking motion constantly via a separate, always-on coprocessor, allowing the main processor to snooze, reducing unnecessary battery drain [9].

Another device by Apple, the iPod nano shown in Figure 4, in a 2012-year-released generation, used a built-in accelerometer to give feedback on workouts by tracking walks and runs. In addition, it was possible to connect any compatible heart rate sensor to the iPod, enabling collection of cardio performance during runs or walks. Thanks to it's small size, it was possible to clip the iPod to a person's shoe, jacket or any other clothing piece [10].

Figure 4. iPod nano with it's clip extended [10].

In this thesis, a built-in IMU in an iPhone 12 Pro Max was used to measure acceleration in a single axis. By processing this data, useful feedback values including energy spent, maximum force applied and number of repetitions for strength training was found.

1.4 Structure of the Manuscript

The thesis is divided into six chapters which:

- introduce the topic
- describe relevant studies
- give an overview of the methodology
- describe data processing implementation and results
- summarize the created software solution
- bring out emerged discussion points and possible future developments.

The thesis is written without the use of any Large Language Model (LLM).

2. Literature

In this chapter, research on similar topics is described, with measurement techniques and findings. It is shown how an Inertial Measurement sensor was used in classification of exercises with dumbbells, in the validation of proper squatting technique and in classification of bodyweight exercises and repetition counting.

A lot of the related literature solves classification problems and repetition counting in different applications, mostly gathering acceleration data from bodyweight workouts or freeweight exercises with barbells or dumbbells, enabling classification between different exercises, techniques and separating repetitions in acceleration logs. Most of the work found also gathers acceleration data from three axes on bodies that move freely in three dimensions. However, research about calorie counting for strength exercises is scarce. In addition, use of cable machines and other training methods for single-axis motion metric gathering is also hard to find.

2.1 Classifying Exercises Performed on Dumbbells

An article published in 2021 describes a method to distinguish and count repetitions of six different exercises performed with free weights. For the study, hexagonal hex dumbbells were used, to which a Razor IMU sensor was attached [11]. Figures 5, 6 and 7 respectively show the used dumbbell prototype and the three basic and three complex analyzed strength exercises.

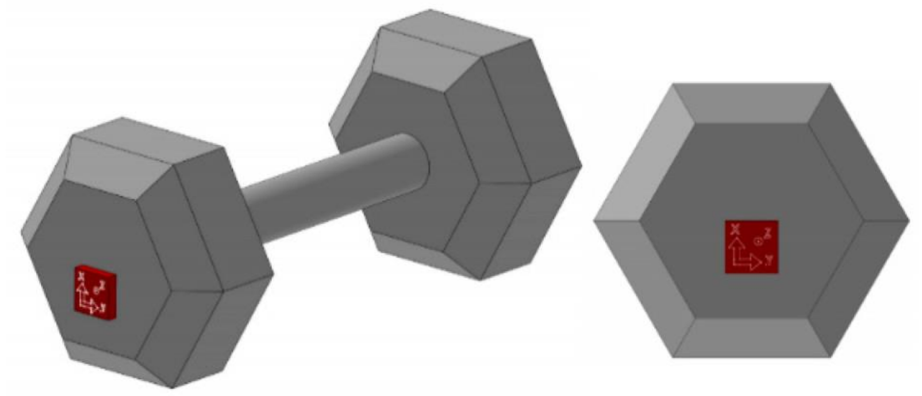


Figure 5. Hex-dumbbell prototype with an attached IMU [11].

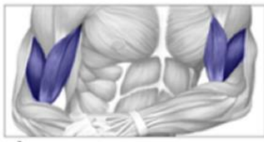
NAME (Mode)	Action	Active muscle
Biceps (1)		
Deltoid (2)		
Triceps (3)		

Figure 6. Three basic exercises [11].

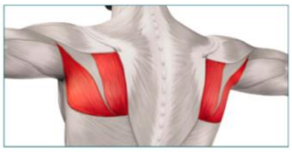
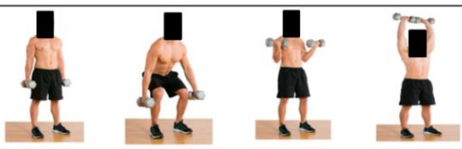
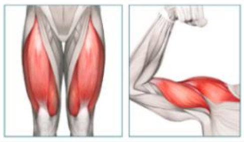
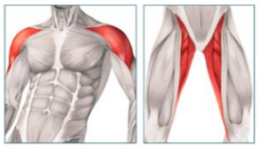
NAME (Mode)	Action	Active muscle
Shoulder(Supraspinatus, infraspinatus) (4)		
Squat & Press (Quadriceps, biceps, deltoids) (5)		
Side Lunge with Sword Draw(Deltoids, adductors) (6)		

Figure 7. Three complex exercises [11].

Exercises were classified by two different algorithms, a ROM (Range of Motion) method, and an SVM (Support Vector Machine) method, the latter of which achieved high accuracy in the classification of six exercises using acceleration and angular velocity data, respectively 100%, 98%, 100%, 99%, 100% and 97 %. In addition, when counting repetitions, combined data from linear acceleration and angular velocity were used, thus making repetition counting more robust than when using only linear acceleration [11].

2.2 Classifying Technique Errors in Bodyweight Squats

An article published in 2017 describes how IMU sensors attached to the body of the exerciser were used to validate the correctness and classify different mistakes in performing a bodyweight squat [12]. An incorrect and physically damaging technique when performing a squat can be, for example:

- heels rising from the ground
- knees angled incorrectly
- too much flex in hips and torso.

Squat techniques were divided into six classes, where one class is a squat with correct technique, the remaining five were squats performed with improper technique [12]. 77 participants aged 16-40 who had prior knowledge of correct squat technique took part in the study. When dividing the performances into six classes, 80% accuracy, 75% sensitivity and 96% specificity were achieved. However, the results were significantly better for binary classification into correct and incorrect technique, achieving 98% accuracy, 96% sensitivity and 99% specificity. In addition, classification results were analyzed using five, three, two, and one IMU sensor, with binary classification performing at a high accuracy with only one IMU sensor placed on the shin. The diagram of all possible IMU positions used is shown in Figure 8.

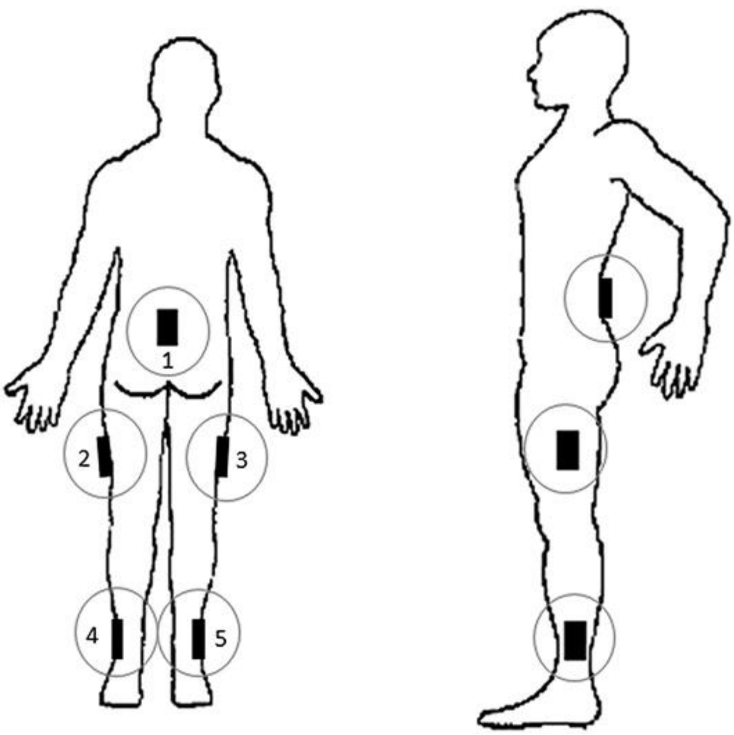


Figure 8. Positions of five different IMU sensors on a person's body [12].

2.3 Counting Repetitions with a Chest-Mounted Sensor

A paper published in 2019 [13] proposes a method to recognize if an exercise is being done and classify it between four different bodyweight exercises:

- pushups
- situps
- squats
- jumping jacks.

A deep learning, Convolutional Neural Network (CNN) algorithm was implemented, achieving a 90.6% accuracy [13]. Most of the mismatches in exercise classification were between pushups and no exercise, and between situps and squats. In addition, Principal Component Analysis (PCA) and peak detection were used to count repetitions once the workout type was recognized. Across the four different exercises, the average detection accuracy of repetitions was 97.9%, with some false negatives occuring in pushups and jumping jacks, and false positives occuring in situps and squats.

Acceleration data was gathered [13] over a total of 583 exercise repetitions, performed by 10 subjects. The data was gathered using a single chest-mounted Movesense acceleration sensor shown in Figure 9, with a 52 Hz measuring frequency. There were two major causes behind using just a single sensor on the chest, one being a potentially comfortable usability for people who would want to use this solution in their workouts; second being the fact that a preliminary study showed the chest as the best possible accelerometer position for detecting and recognizing exercises and counting repetitions when using just a single accelerometer.

Figure 9. Movesense sensor with a size comparison to a 2 EUR coin [13].

2.4 Step Counting in Forensics

In 2019, an article [14] investigated the accuracy of steps and covered distance registered by the Health application running in different conditions on an iPhone 6, iPhone 7 and iPhone 8. For five subjects, carrying location and walking distances were varied. Distances covered and steps taken were also measured manually. The goal was to validate the accuracy and reliability of step counting and distance measurement of an iPhone for proper use in forensic analysis.

As a result, it was shown that the phone's registered steps align with the manually measured step counts, with an average of 2% error [14]. However, registered distances deviated up to 40% from the manually measured true values. To add, from the results it was clear that hardware differences between these three iPhone models were insignificant.

2.5 Walking Recognition and Intensity Estimation

A paper published in 2014 describes a system to recognize gait [15] and if the person is indeed walking, a method to measure the intensity of the walking exercise. For data collection, an iPhone 4 smartphone on a person's waist was used, equipped with separate 40 Hz STMicro gyroscope and an accelerometer, gathering data from 10 different subjects: five of them male and five female. For algorithm verification, 100 walking data records were recorded with participants in every test walking along a 50 m straight line while maintaining a speed of 1.56 m/s, and for baseline comparison, a Leica Disto D3ABT range finder was used. In other experiments, participants were made to walk, run, walk upstairs and walk downstairs.

To conclude, the result of this work was a system for walk intensity recording and gait recognition, which involved exercise posture capturing and exercise intensity estimation. The real user motion acceleration excluding the effect of gravity was used to estimate exercise intensity. Furthermore, the direction information obtained from the gravity data of the accelerometer was used to output motion posture and direction angle for gait recognition. The final recognition accuracy of gait was over 90%. In addition, the work states that an improvement of walking exercise intensity estimation accuracy was achieved, when compared to past research methods [15].

3. Methodology

The following gives a short overview of how relevant values for feedback on a strength exercise performed on a cable machine can be found from acceleration data, showing the formulas used. In addition, practical questions like noise reduction and repetition counting are described. Furthermore, a description of implementing these methods is given.

3.1 Essential Principles

It is assumed that the device used for measurement is not under acceleration and not in motion in it's starting position. The device's acceleration values used are from a single axis. In addition, the total mass of the weights used is known beforehand, in order to enable finding spent energy and maximum force applied.

Acceleration is defined as a rate of change of velocity. From the definition of acceleration, velocity *V* can be found by integrating acceleration over time:

$$V(t) = \int a(t)dt + C_1$$

Similarly, we can use a formula to find the position *x* of the body by integrating velocity over time:

$$x(t) = \int V(t)dt + C_2$$

By knowing the mass of the weight stack *m*, assuming that the starting acceleration a_0, velocity V_0 and displacement change Δd are equal to zero and that the exercise is performed on the surface of the Earth, the energy expenditure *E* can be found from:

$$E = m \times a \times \Delta d$$

To find the maximum force *F* applied at a single moment by the exerciser:

$$F = m \times a$$

3.2 Practical Issues

With acceleration data processing, issues from real-life applications arise. The acceleration sensor may record noise due to vibrations of the surroundings, weights and other minor motions. Such noise is slightly different from the true value and needs to be filtered. Methods to remove noise like low-pass filtering and moving average smoothing were tried out, where moving-average method with a window size of 5 was chosen. This enabled to filter out noise resulting from unwanted vibrations, while retaining the acceleration data of the weight's movement. The implementation in program code and resulting values found from these formulas are described in the following chapters.

3.3 Implementation Details

Two distinctive implementations of the method were produced: one in Jupyter Notebooks for initial testing and faster development, and another in a Rust web server for a potentially scalable solution for data processing.

3.3.1 Jupyter Notebook

In order to validate usability of the methodics, to visualize data and calculated metrics, Jupyter Notebooks was used. There, a notebook's main points can be described as:

- reading raw acceleration data file
- applying noise filtering
- counting repetitions from filtered acceleration with peak detection
- for every timestep, calculating respective values for velocity and position
- finding upward motions from position data
- calculating energy expenditure from upward motions.

3.3.2 Server and User Interface

As a secondary goal, a software solution was developed, thanks to which it is possible to receive feedback about the strength exercise performed on the cable machine from the measured acceleration data of the smartphone. The software allows a user to upload acceleration data in .csv form through the user interface implemented in React, after which the data is handled by a web server implemented in Rust. The server implementation used the same methodics as in the Jupyter Notebook's implementation. The feedback shows, among other things, the number of repetitions and expended energy, in addition to plots of acceleration, velocity and position of the point mass.

4. Experiments and Results

This chapter goes into detail about the measurement of data when moving weights. The lat pulldown exercise and the cable machine on which the exercise is performed are described. An overview of the hardware, software and location of the measuring device during the measurement is provided. Data recording is reviewed and a section of the collected data is shown.

4.1 Devices and Software

For the purpose of this thesis, a TechnoGym cable machine, an iPhone 12 Pro Max and a PhyPhox software application were used, which are described in more detail.

4.1.1 TechnoGym Cable Machine

Measurements were performed on a TechnoGym Cable Stations 4 with a product code MB84, a photograph of which is shown in Figure 10. The machine can be used by up to four people simultaneously, as several attachments and height-adjustable attachment points allow performing lat pulldowns, cable rows, bicep curls, cable crunches, and more [16].

Figure 10. TechnoGym Cable Stations 4 [16].

4.1.2 iPhone 12 Pro Max

An iPhone 12 Pro Max smartphone was used for the measurements described in the work. Inside the iPhone 12 Pro Max is a Bosch Sensortec IMU sensor with a measurement frequency of 100 Hz, with an unknown specification and product code [17].

The used smartphone in a silicone case was installed on top of the top weight plate of the training machine in a way that the phone was horizontally fixed between the slider of the training machine and the weight stack attachment, with the aim of measuring the movement of the device on the z-axis and minimizing movement on the other axes. The setup of this hardware is shown in Figure 11.

Figure 11. iPhone 12 Pro Max on top of Cable Stations 4 weight stack.

4.1.3 PhyPhox

PhyPhox, an open source iOS application developed by the 2nd Institute of Physics at RWTH Aachen University, was used to measure acceleration data [18]. A screenshot of the application running on an iPhone 12 Pro Max is shown in Figure 12. The application [19] provides an opportunity by using a smartphone's built-in sensors to measure, for example:

- linear acceleration
- angular velocity
- air pressure
- sound frequency and volume.

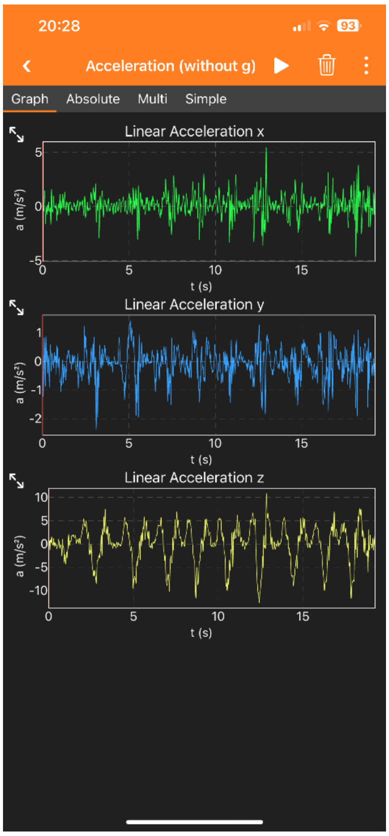


Figure 12. Screenshot of PhyPhox displaying logs of acceleration.

4.2 Collection

The main test data collection took place on the previously described exercise machine, using the iPhone 12 Pro Max smartphone fixed to the weights. Various data points were recorded:

- acceleration logs from PhyPhox application
- repetition count
- mass of the weight stack
- distance travelled by the smartphone.

Some of the author's measured test data is accessible at a Github repository[1], with a total of 10 acceleration logs. The sizes of gathered raw data files fall in a range of 200 to 400 kilobytes. Table 1 shows a slice of data from a measurement started on 17.03.2024 at 19:47:45 with a 100 Hz sensor. 10 repetitions of lat pull-downs were performed to train the *latissimus dorsi*, having 30 kg of weight plates attached. The plot of "Linear Acceleration z (m/s^2)" is also shown in Figure 13. During the exercise, the weight plates and thus the measuring device moved up 0.5 meters and down the same distance for each repetition.

Table 1. First five rows of acceleration data logs.

Time (s)	**Linear Acceleration x (m/s^2)**	**Linear Acceleration y (m/s^2)**	**Linear Acceleration z (m/s^2)**	**Absolute acceleration (m/s^2)**
0.004849	-0.017460	0.086111	-0.015137	0.089158
0.014848	0.006514	0.085409	-0.008400	0.086068
0.024846	0.015955	0.081478	-0.008698	0.083480
0.034844	0.010618	0.072818	-0.037891	0.082771
0.044843	0.021263	0.059325	-0.044332	0.077051

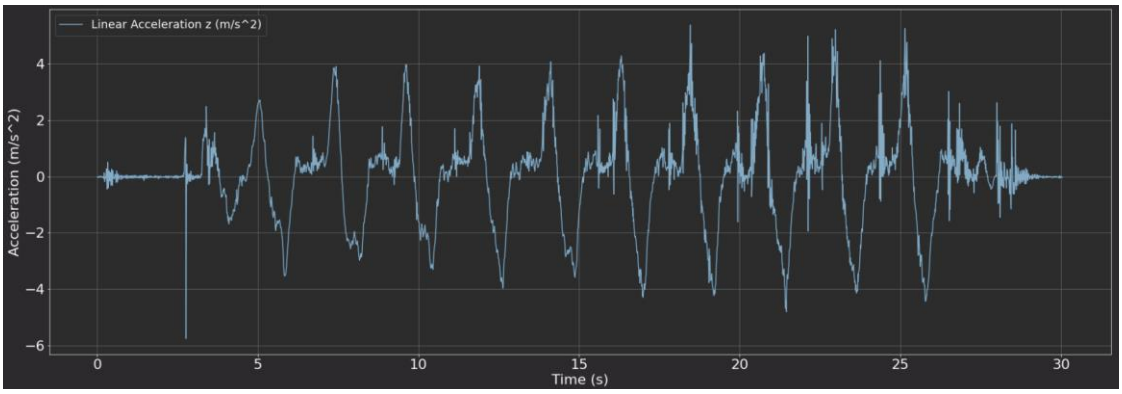


Figure 13. Acceleration logs on z-axis. 10 repetitions, mass of 30 kg, distance of 50 cm.

4.3 Data processing

Data cleaning, processing and analysis are described below. The goal is to fetch from the raw acceleration data, the:

- energy expenditure

[1] https://github.com/raltm2e/imu_phyphox/tree/master/data

- repetition count
- maximum force exerted.

In the data analysis, it was assumed that the movement takes place on the z-axis. Under the same assumption, both the x- and y-axis acceleration data were ignored, since there is mainly noise there, and it is difficult to extract useful feedback about the movement of the weight. The following describes the processing of the z-axis acceleration data for the performance measured on 17.03.2024 at 19:47:45.

4.3.1 Noise

As described in chapter 3.2, high-frequency noise is smoothed out by using a moving-average method. The results of this are shown in Figure 14, with raw data depicted in blue and filtered data in orange.

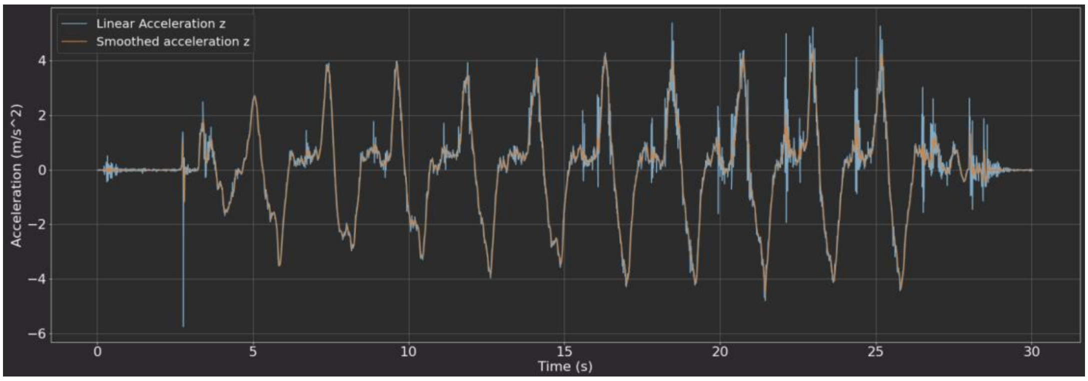


Figure 14. Raw (blue) and filtered (orange) acceleration data.

When measuring the exercise, the start and end of the acceleration data is unnecessary information, since the exerciser spends time to reach the starting position of the exercise and stop the measurement after finishing the final repetition. On this test data, 4.5 seconds were cut from the beginning and 3.0 seconds from the end when performing the exercise. Figure 15 shows the slices of data in blue that were trimmed from the previously filtered acceleration logs.

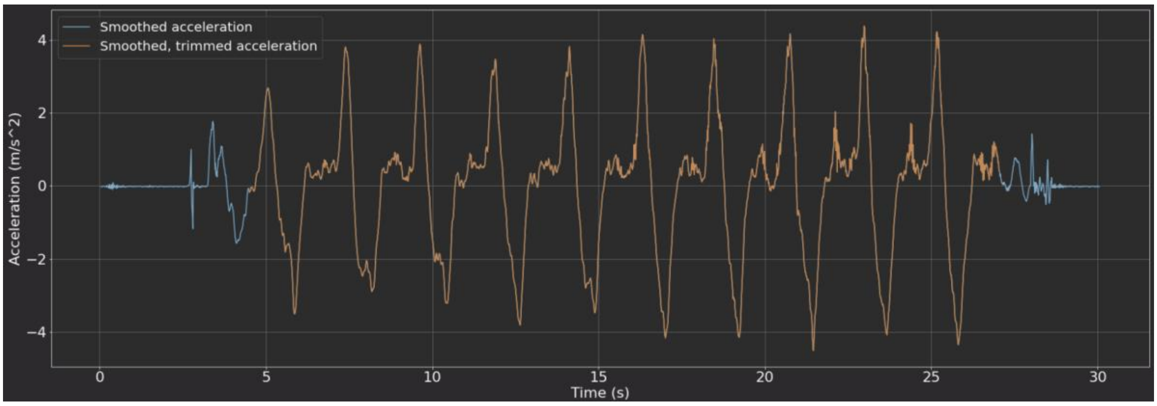


Figure 15. Acceleration with start and end trimmed off, in orange.

4.4 Velocity and Position

To find the energy spent by the exerciser, it is first necessary to find the distance traveled by the weights. As described earlier, the mass is known beforehand, in this example case the weight stack's mass was 30 kg. For each measured moment of time, the instantaneous velocity of the body was found, from which the distance traveled by the body could be found, and knowing the mass, the energy spent to move the mass could be found. Figures Figure 16, Figure 17 and Figure 18 show acceleration, velocity and position of the measuring device on z axis in time, respectively. These values are all found on the noise-filtered and trimmed acceleration data.

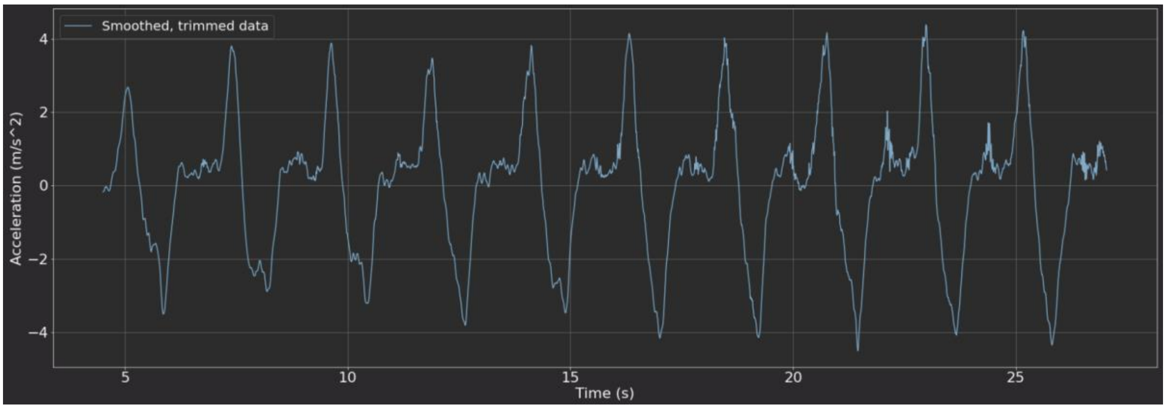


Figure 16. Z-axis acceleration after trimming.

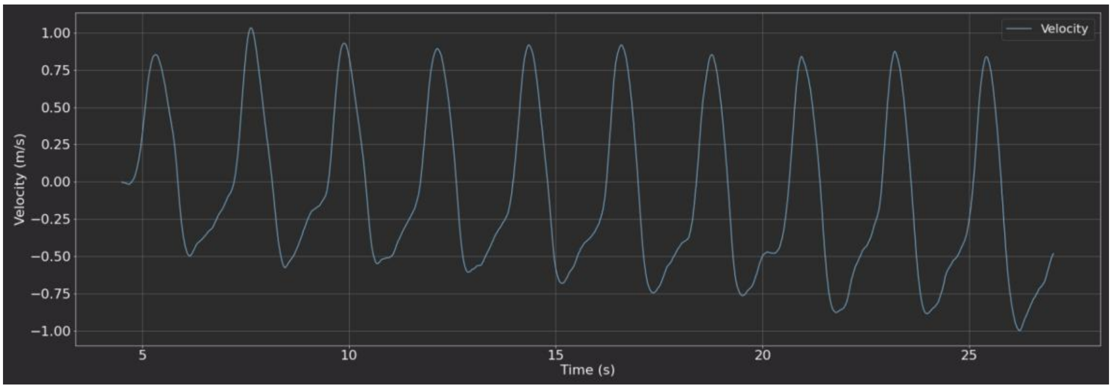


Figure 17. Z-axis velocity.

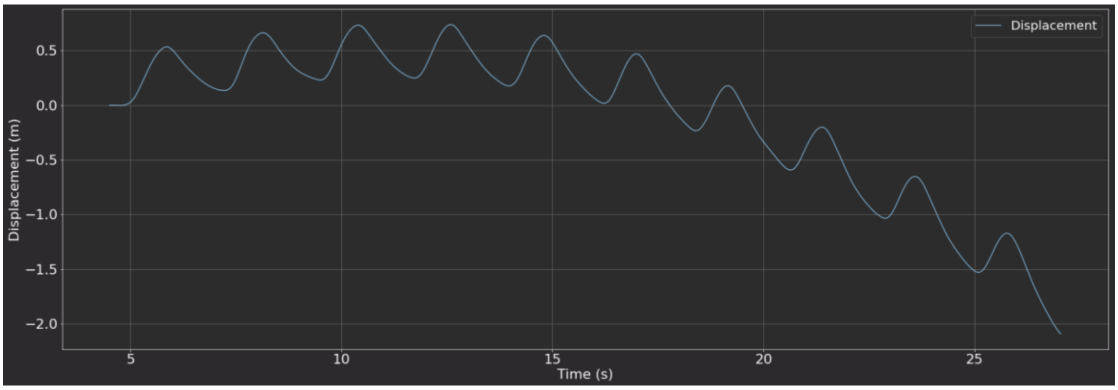


Figure 18. Z-axis position.

4.5 Repetitions and Energy

Finding the number of repetitions was tried out in two ways: by counting the peaks in filtered acceleration data, or by counting the cycles of upward movements by position on the z-axis. The peak detection on acceleration data proved to be more robust and was used for repetition counting. On this example data, it was found that 10 repetitions were performed, as is plotted on Figure 19.

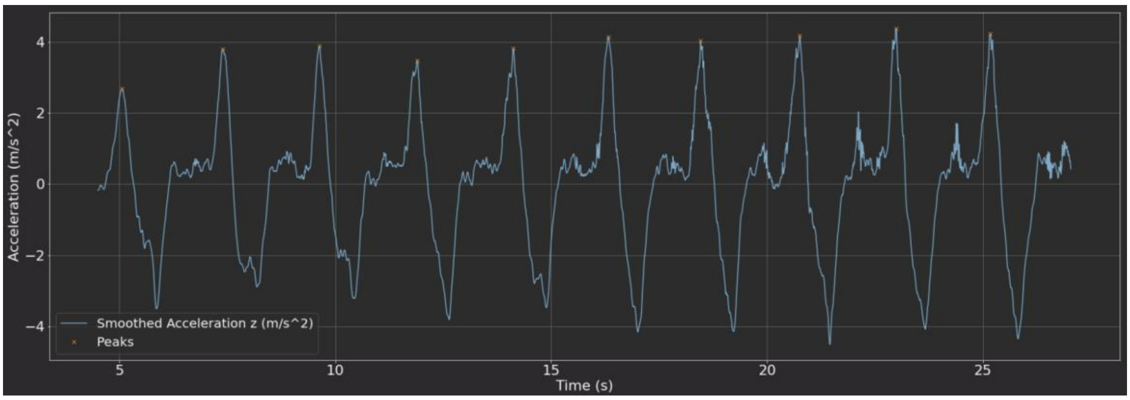


Figure 19. Peaks detected on acceleration data.

For energy consumption, the upward motions of each repetition were used, displayed in red in Figure 20. Thanks to knowing the mass of the body, it was found that the total energy spent to move the weight stack upwards for 10 repetitions was 0.3188 kCal.

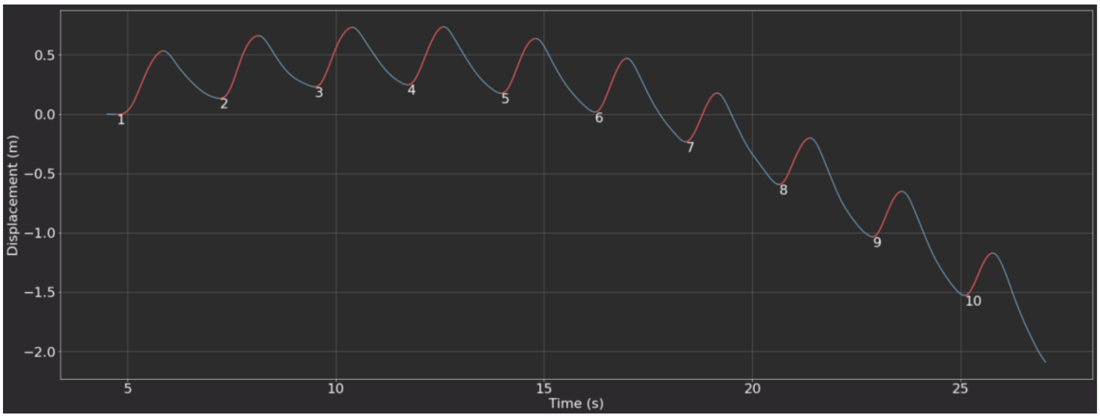


Figure 20. Z-axis position with upward motions.

4.6 Force

It is also possible to find the maximum force applied at one moment from the movement that took place in the exercise, simply by finding the highest z-axis acceleration value. Since the mass of the body is also known, it is possible to easily find the force applied by the exerciser. The maximum force found applied to move the 30 kg weight stack in the aforementioned acceleration data was during the 9th repetition, with a value of 425.56 N.

4.7 Comparison with Baseline, Proof of Concept

To validate the real-life correspondence of the processed results, the vertical distance traveled by the measuring smartphone was measured at each repetition. Knowing the mass of the weights moved, the difference between the potential energies of the lower and upper positions of one repetition was found, which can also be interpreted as the energy expenditure of the repetition. The energy losses arising from friction are not taken into account, since the energy consumption has also been found from the smartphone's acceleration data on the same assumption.

$$E = m \times g \times h$$

Based on moving a 30 kg mass by 0.5 m at each repetition, it was found that the total energy consumption from the data obtained from the smartphone and the difference in potential energy by comparison fall to the same order of magnitude. Going back to the exercise with the start time of 17.03.2024 at 19:47:45, the energy expenditure found from the acceleration data is

1333.9 J ≈ 0.3188 kCal for pulling up the weights 10 repetitions. The energy consumption for lifting the same weight for 10 repetitions, found according to the change of potential energy, is 1471.5 J ≈ 0.3517 kCal. The difference between the energy consumption found from the measured data and the calculated energy consumption was 9.80965%. Below, Table 2 summarizes the use of the same methods on additional acceleration data, gathered using the same hardware by the same person performing a lat pulldown exercise.

Table 2. Method results on additional acceleration logs.

Measurement start date and time	**Mass (kg)**	**Counted Repetitions**	**Detected Repetitions**	**Baseline Energy (kcal)**	**Calculated Energy (kcal)**	**Max force (N)**
17.01.2024, 08:15:45	70	10	11	0.8203	0.5962	963.23
17.01.2024, 08:17:32	70	10	9	0.8203	0.5650	924.52
20.01.2024, 17:52:51	75	10	10	0.8789	0.7028	906.43
20.01.2024, 18:02:19	80	8	9	0.4800	0.4089	1110.32
17.03.2024, 19:05:55	60	10	11	0.7031	0.4176	745.83
17.03.2024, 19:13:02	50	10	11	0.5860	0.3433	624.60
17.03.2024, 19:49:39	50	10	10	0.3750	0.2521	664.48
17.03.2024, 19:53:49	30	10	12	0.2250	0.1092	378.44
17.03.2024, 19:56:31	50	10	12	0.3750	0.3507	661.21

It must be noted that moving the weight stack by a precise distance was not the primary focus in these data logs, and as such, differences between baseline and calculated energy consumption exist. To add, in every case where the detected repetition count was higher than actual, there was an agressive drop of the weights which caused a peak in acceleration that was counted as a repetition even in moving-average-filtered data. More of these arised issues are expanded and explained in detail in Open Challenges. Furthermore, although there is not a baseline value to compare the detected maximum force to, it is visible that the applied force is largely dependent on the mass of the weights.

As the main goal of the work, it was shown that with some concessions, it is feasible to use the measured data of a smartphone placed on top of a weight plate to receive feedback in the form of energy expended, maximum force applied and number of repetitions performed.

5. Software

For a more convenient way to get training feedback data, a web application was created for uploading data in .csv form from the PhyPhox application. The created user interface displays numerical indicators, including the number of repetitions and energy consumption. In addition, the filtered acceleration sensor data and the point mass movement trajectory are presented with charts.

A server-side application was created using Rust and HTTP endpoints to upload, process and return data. The web client for uploading files and displaying visualizations is implemented using React. A repository with the source code can be found on GitHub[2]. An overview of the architecture is shown in Appendix 2.

5.1 Server

The server side is implemented in the Rust programming language, using Actix framework for endpoints. Running it is simple thanks to an easily deployable and publicly available Docker image.

5.1.1 Rust

Rust is a compilable language with the first stable version (1.0) released in 2015 by Mozilla Research. It has the advantages of memory safety, type safety, speed and a compiler with informative feedback compared to existing technologies. In addition, the built-in Cargo package management system allows a fluent development experience. The language has gained popularity in recent years due to its ability to efficiently handle parallel programming tasks, making it suitable for building systems with high reliability requirements [20].

HTTP endpoints are built using the Actix framework. It is one of the common Rust web frameworks that provide Rust's inherent type safety, performance, and easy scalability. In addition, Actix supports various middleware, which simplifies the creation of complex web applications [21].

5.1.2 Docker

Docker is an open source platform that allows to build, deliver and run applications in containers. A container is a lightweight, self-contained, executable software package that

[2] https://github.com/raltm2e/imu_phyphox

contains everything it needs to run: code, configuration files, and dependencies. Using Docker containers, it is possible to package an application's source code with all its dependencies into an easy-to-run application, making deployment in different environments easier and less machine-dependent [22].

The Docker image required to run the server can be found on Dockerhub[3]. The Dockerfile content used to build the image is found in Appendix 3.

5.2 User interface

The web client is implemented using the React framework. The User Interface (UI) provides a way to check if the data analysis server is running and can be accessed, displaying „OK!“, if a status response from the server is received, as is also depicted in Figure 21.

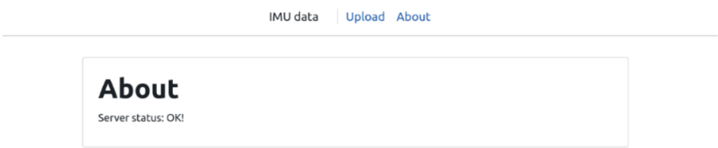


Figure 21. Screenshot of server status validation page.

In the web user interface’s uploading page shown in Figure 22, the user needs to enter the parameters used in the exercise:

- mass of weights
- noise level (low/medium/high)
- accelerometer logs in csv format.

The choice of noise level depends on the noise filtering of the acceleration data, where the filtering is weaker at low noise levels.

Upon successful data upload, the following is displayed to the user as feedback for the exercise:

- repetition count
- energy expenditure
- acceleration plot
- velocity plot
- position plot.

[3] https://hub.docker.com/r/raltm2e/imu-backend

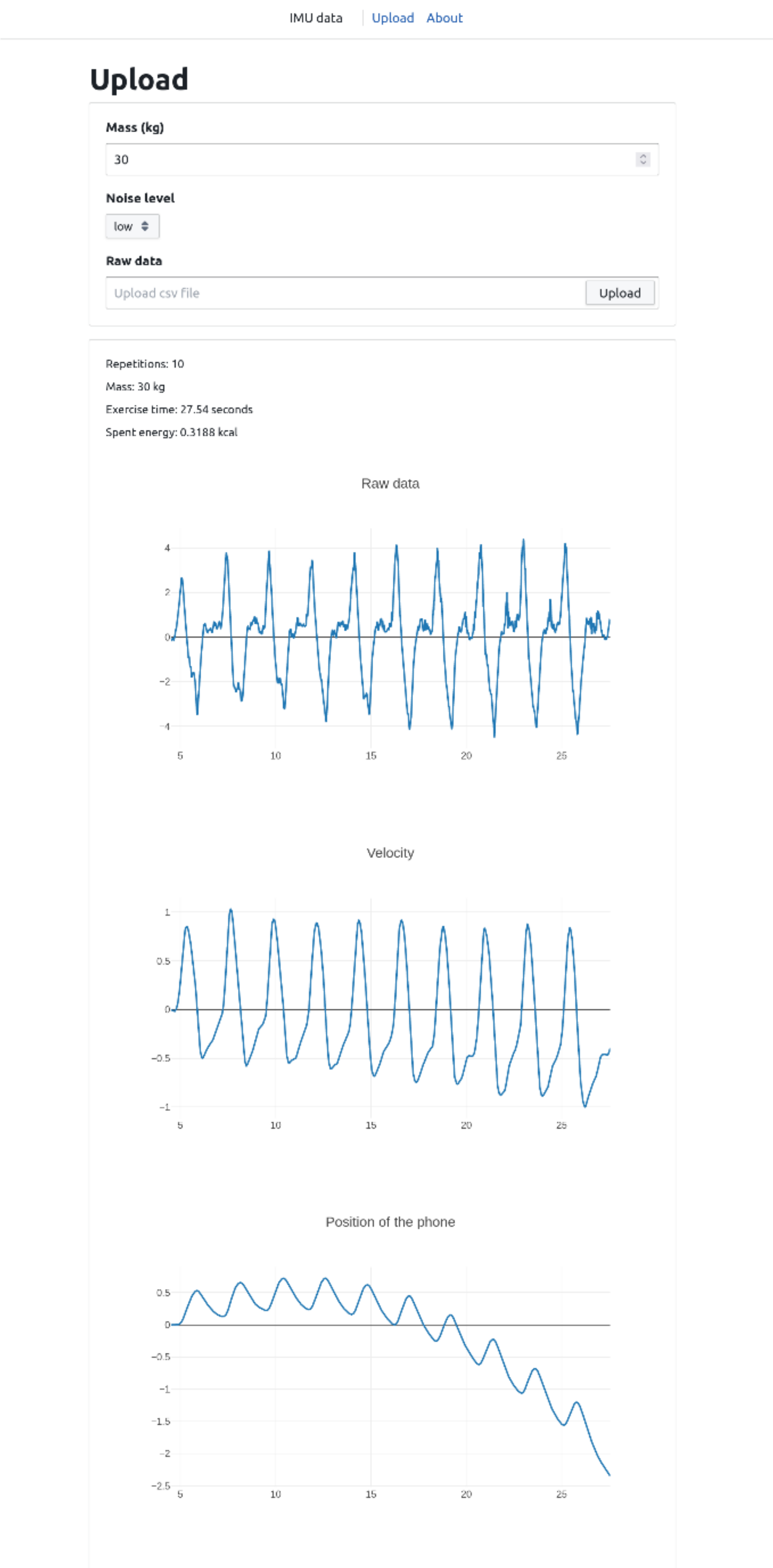


Figure 22. Screenshot of UI displaying feedback after a successful acceleration data upload.

5.3 Hardware Specifications

This software was developed and run on a 6-core AMD Ryzen 5 5600X processor [23] with 16 gigabytes of memory, using both Windows 10 and Ubuntu 22.04 LTS operating systems. The server side Docker image has also been run on an Azure virtual machine with a single-core processor and 2 gigabytes of memory with no issues arising from a single user’s data processing.

6. Open Challenges

During the work, several points of concern emerged, which are described in detail in the following chapter.

6.1 Noise

The cable machine described in the work and the training area itself can produce noise, which may affect the measured acceleration data and processed results. Main sources of noise are described and in some cases, possible ways to mitigate noisiness are mentioned.

6.1.1 Machine's Vibrations

The used cable machine has a lot of moving components, thus creating a potential source of vibrating motions, which could be transmitted to the accelerometer. Possible factors that can cause such vibrating, shaky movement, are:

- Sliders rubbing excessively and unevenly
- Large tolerances between sliders and weight plates
- Loose pulleys

To minimize the noise from the sliders and pulleys, it is necessary to make sure that the weights move smoothly by using high-quality and regularly maintained cable machines.

6.1.2 Dropping Weights

From previously shown detected repetition counts, it is visible that dropping the weights causes the detected repetition count to increase. However, filtering it out is not trivial as it is possible for the training subject to be strong enough to move the weights during a repetition with the same acceleration as can happen from a drop.

When performing the exercise, it may happen that between repetitions, the weight plates fall against the ground to the initial position, causing a relatively high acceleration of the measuring device for a short moment. Although filtering can clean such noise from the data, it depends a lot on the measurement frequency of the acceleration sensor. The lower the frequency of measurements, the more difficult it is to filter out short-term noise.

Such short-term high acceleration can also be caused by another exerciser in the gym, whose heavy barbell dropping on the floor can cause oscillations in the measuring device.

6.1.3 Dimensional Differences

The dimensions of the cable machine and the smartphone used in this work matched well, due to which, thanks to the silicone case, the phone could be fixed horizontally on the weight plate. However, it may be more difficult to fix the phone using a different cable machine or a smartphone of a different size, so it may happen that the data measured by the acceleration sensor is not usable due to unwanted movement or a tilted position of the phone.

6.1.4 Start and End Trimming

Currently, the accelerometer data is cut off from the start and end by a specified period of time to account for the time spent by the exerciser to assume the starting position of the exercise and stop the measurement from the end position. However, the time spent at the beginning and end of the exercise may vary depending on the equipment and the exerciser himself, so a more dynamic solution would be useful to find suitable values for distinguishing the repetitions of the exercise from the unnecessary beginning and end of the measurement.

6.1.5 Acceleration Drift

The main problem with an accelerometer is the accumulation of its error over time, especially when the acceleration value is used for positioning [24]. As a result, the position of the weight plate found during the last repetition of the strength exercise may have deviated significantly from reality.

6.2 Real-life Distance Measuring

When measuring the weight stack's travelled distance per repetition for a baseline comparison of energy expenditure values, it is difficult to verify if the weight stack was in fact moved for the same distance in every repetition. For example, if a person does 10 repetitions, he/she may be more tired by the tenth repetition compared to the first, thus moving the weight stack not that much as in the first repetition. This can affect the baseline comparison results negatively. Gathering more data from different people performing an exercise could mitigate these mismatches.

6.3 Additional Data

As discussed, dimensional variables of both the smartphone and the cable machine in use can affect gathering of the acceleration data. In addition, it is likely that two different people performing the same exercise can cause differences in measured acceleration data, even if the hardware used is the same. To improve robustness and to validate that the methodology described has potential to be used by others, collecting more test data should be done, with exercises performed by people of various physique levels and strength training experience.

6.4 Potential Future Developments

At the moment, the completed solution can be used personally, but for wider use, a separate mobile application should be developed, a sturdy way to attach the phone should be used, and if possible, acceleration measuring with different phones should be tried out on the most common cable machines. In addition, a dedicated mobile application and a specially designed phone mount would improve usability by a margin.

6.4.1 Dedicated Mobile Application

At this point, to receive training feedback, there are many preliminary steps also shown in Appendix 1 that will be needed to do to fetch numerical and plotted feedback of a workout.

The four necessary steps are:

1. Measure the acceleration of the exercise with the PhyPhox app
2. Save and export measured data
3. Upload acceleration data to the server via UI
4. Get feedback from UI.

This multi-step process is too tedious and error-prone for it to be widely useable. A separate mobile application for both iOS and Android operating systems has great potential to increase usability on almost all smartphones. The application must access the output of the accelerometer to record the sensor logs over time. Data processing and return of feedback training data can be implemented either in a central server or in the mobile phone itself.

For feedback, it is definitely necessary to return more important numerical indicators to the user: number of repetitions, energy consumption and maximum force. In addition, it is worth displaying performance graphs to the user on the phone itself. A power meter displaying the applied force in real time would be an attractive feature. User management with proper authentication and user-based log saving would also be needed.

6.4.2 Universal Phone Mount

In order to enable measurements on multiple cable machines with smartphones of different dimensions, it would be useful to develop a universal smartphone mount for the top weight plate. To reduce noise, it would be wise to use vibration-absorbing materials. In the author's opinion, it is worth investigating the use of cell phone mounts used on motorcycles, such as Quadlock, for mounting on the weight plate, as such mounts are often designed to absorb high-frequency vibrations in order to protect the phone's camera and other components on the constantly vibrating handlebars of a motorcycle. [25].

Conclusion

In this thesis, the data processing pipeline of acceleration data from an IMU sensor during lat pulldown exercises on a cable machine was explored. Using the PhyPhox application on an iPhone 12 Pro Max, acceleration along the z-axis was measured, focusing on vertical movement. Features such as energy consumption, repetition count and maximum force applied were extracted. In addition, a software solution was created for smoother acceleration data uploading, processing and visualization of results.

Through this research, insights were gained regarding the use of a smartphone on a cable machine's weight stack for exercise analysis. Potential sources of noise are mentioned, with recommendations for mitigation. By seeing this thesis as a proof of concept, the use of a smartphone with it's built-in IMU has potential to be beneficial for both athletes and hobbyists, in order to improve their physique thanks to valuable feedback over time from processed exercise data. The challenges listed in chapter 6 are some of the avenues to be explored in the future, in the line of research of this thesis.

References

[1] "Strength Training -," FitnessHealth101.com, 2024. [Online]. Available: http://www.fitnesshealth101.com/fitness/weight-training/strength-training. [Accessed 16 Apr 2024].

[2] L. M. M. Schuler, "The Men's Health Home Workout Bible," Rodale, 2002, p. 40.

[3] J. Fox, "Nutritioneering," 18 Nov 2022. [Online]. Available: https://www.bodybuildingmealplan.com/cable-arm-exercises/. [Accessed 18 Apr 2024].

[4] T. Edwards, "The Lat Pulldown: Benefits, How-To, and Muscles Worked," Healthline, 15 Feb 2022. [Online]. Available: https://www.healthline.com/health/fitness/lat-pulldown. [Accessed 21 Apr 2024].

[5] "Lat Pulldown Standards for Men and Women (kg) - Strength Level," 2024. [Online]. Available: https://strengthlevel.com/strength-standards/lat-pulldown/lb. [Accessed 20 Apr 2024].

[6] F. Laricchia, "Apple revenue streams/segments by quarter 2024 | Statista," Statista, 22 Apr 2024. [Online]. Available: https://www.statista.com/statistics/382136/quarterly-segments-revenue-of-apple/. [Accessed 13 May 2024].

[7] R. C. Johnson, "GPS system with IMUs tracks first responders," 6 Jun 2011. [Online]. Available: https://web.archive.org/web/20121003161057/http://www.eetimes.com/electronics-news/4216978/GPS-system-with-IMUs-tracks-first-responders. [Accessed 14 May 2024].

[8] "Attitude and Heading Reference Systems - A wide range of AHRS," SBG Systems, 2023. [Online]. Available: https://www.sbg-systems.com/attitude-heading-reference-systems-ahrs/. [Accessed 21 Apr 2024].

[9] J. Tanner, J. Morrison, D. James, R. Fontaine, P. Gamache, "Inside the iPhone 5s | Chipworks Blog," Chipworks Inc., 20 Sep 2013. [Online]. Available: https://web.archive.org/web/20140803201521/http://www.chipworks.com/en/technical-competitive-analysis/resources/blog/inside-the-iphone-5s/. [Accessed 13 May 2024].

[10] "Apple - iPod nano - Music with Multi-Touch, FM radio, and more.," Apple Inc., 2012. [Online]. Available: https://web.archive.org/web/20120818233450/https://www.apple.com/ipodnano/features.html#fitness. [Accessed 9 May 2024].

[11] Y. Shiao, T. Hoang and P.-Y. Chang, "Real-Time Exercise Mode Identification with an Inertial Measurement Unit for Smart Dumbbells," 5 Dec 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/23/11521/htm. [Accessed 4 Apr 2024].

[12] M. A. O'Reilly, D. F. Whelan, T. E. Ward, E. Delahunt and B. M. Caulfield, "Technology in Strength and Conditioning: Assessing Bodyweight Squat Technique With Wearable Sensors," *Journal of Strength and Conditioning Research,* vol. 31, no. 8, pp. 2303-2312, 2017.

[13] K. Skawinski, F. M. Roca, R. D. Findling, S. Sigg, "Workout Type Recognition and Repetition Counting with CNNs from 3D Acceleration Sensed on the Chest," in *Advances in Computational Intelligence*, Gran Canaria, 2019, pp. 347-359.

[14] A. B. Jan Peter van Zandwijk, "The iPhone Health App from a forensic perspective: can steps and distances registered during walking and running be used as digital evidence?," *Digital Investigation,* pp. S126-S133, Apr 2019.

[15] B. R. L. Hsiao, Y. Liu, C. Yu, G. E. Jan, Bo-Tang, "Gait Recognition and Walking Exercise Intensity Estimation," *International Journal of Environmental Research and Public Health,* vol. 11, pp. 3822-3844, 2014.

[16] "Cable weight machine: Technogym Cable Stations 4 Connector | Technogym International," Jul 2021. [Online]. Available: https://www.technogym.com/marketing-support/download/A642EC95-08B6-4EB9-B611-ED847DC2318A. [Accessed 17 Apr 2024].

[17] T. Dixon, "iPhone 12 and 12 Pro Teardown - iFixit," 20 Oct 2020. [Online]. Available: https://www.ifixit.com/Teardown/iPhone+12+and+12+Pro+Teardown/137669. [Accessed 5 Apr 2024].

[18] "phyphox - Physical Phone Experiments," [Online]. Available: https://phyphox.org/. [Accessed 8 Apr 2024].

[19] "phyphox/phyphox-ios: Physical Phone Experiments (iOS app)," 2024. [Online]. Available: https://github.com/phyphox/phyphox-ios. [Accessed 9 Apr 2024].

[20] "Rust Programming Language," Rust Team, [Online]. Available: https://www.rust-lang.org/. [Accessed 11 Apr 2024].

[21] "Actix," The Actix Team, 2024. [Online]. Available: https://actix.rs/. [Accessed 14 Apr 2024].

[22] "Docker: Accelerated Container Application Development," [Online]. Available: https://www.docker.com/. [Accessed 15 Apr 2024].

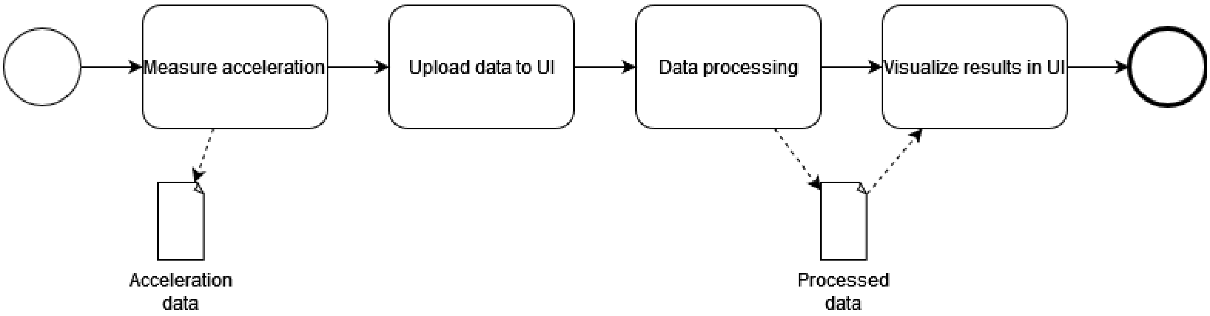
[23] "AMD Ryzen 5 5600X Desktop Processors," Advanced Micro Devices, Inc., 2024. [Online]. Available: https://www.amd.com/en/products/processors/desktops/ryzen/5000-series/amd-ryzen-5-5600x.html. [Accessed 14 May 2024].

[24] "IMU Specifications Explained - VectorNav," 2024. [Online]. Available: https://www.vectornav.com/resources/inertial-navigation-primer/specifications--and--error-budgets/specs-imuspecs. [Accessed 19 Apr 2024].

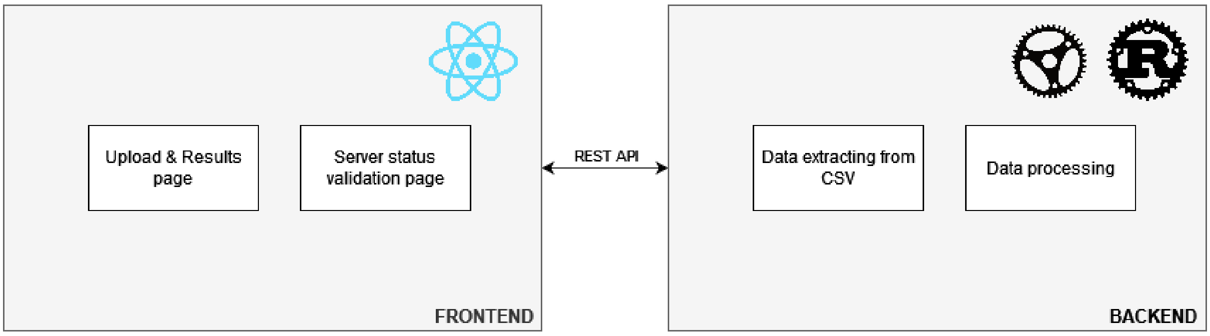
[25] "Motorcycle - Vibration Dampener - Quad Lock Europe - Official Store," Annex Products PTY LTD, 2024. [Online]. Available: https://www.quadlockcase.eu/products/vibration-dampener. [Accessed 19 Apr 2024].

Appendices

Appendix 1 – User flow



Appendix 2 – Software stack



Appendix 3 – Dockerfile used to build server image

```
FROM rust:1.70-slim-buster as build
RUN USER=root cargo new --bin imu-backend

WORKDIR /imu-backend
COPY ./Cargo.toml ./Cargo.toml

RUN cargo build --release
RUN rm src/*.rs

COPY ./src ./src
RUN cargo build --release
FROM debian:buster-slim

COPY --from=build /imu-backend/target/release/imu-backend .
EXPOSE 8080
CMD ["./imu-backend"]
```

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