Department of Engineering Cybernetics

IMU Based Movement Analysis During Manual Wheelchair Propulsion

Specialization Project

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Abstract

Most algorithms predicting energy expenditure are created based on data from the able-bodied population. Due to this, most commercial activity trackers fail to correctly estimate energy expenditure for manual wheelchair users. This study investigates classification of movement intensity during wheelchair propulsion based on IMU data.

The extracted features are hand cycle times and the number of cycles within a 30 second window. To check the validity of the features from the IMU, the same features will be extracted from motion-captured trajectories as a reference. Correlation between features from the IMU and the reference trajectories became stronger with increasing activity intensity, and results show that a lower cycle time correlates to a higher movement intensity.

Motion captured trajectories were split into individual cycles which were averaged over a 30 second time window. Comparing the average trajectories based on intensity levels and different inclines on a treadmill showed that there is more variability in trajectories for lower intensity levels. Results suggest that the variability, or the lack thereof, is of relevance in predicting energy expenditure.

Sammendrag

De fleste algoritmene som estimerer energiforbruk er laget basert på data fra den fysisk friske befolkningen. På grunn av dette svikter de fleste kommersielle aktivitetssporere i å estimere energiforbruket for brukere av manuelle rullestoler på en presis måte. Denne studien undersøker klassifisering av bevegelsesintensitet under rullestolfremdrift basert på IMU-data.

De uthentede egenskapene er håndsykeltider og antall sykler innenfor et 30-sekunders vindu. For å sjekke gyldigheten av egenskapene fra IMUen, vil de samme egenskapene også bli utvunnet fra bevegelsesfangede baner som referanse. Korrelasjonen mellom egenskapene fra IMUen og referansebanene ble sterkere med økende aktivitetsintensitet, og resultatene viser at en lavere sykeltid korrelerer til en høyere bevegelsesintensitet.

Bevegelsesfangede baner ble delt opp i individuelle sykler som ble tatt gjenommsnitt over i et 30-sekunders tidsvindu. Sammenligning av gjennomsnittlige baner basert på intensitetsnivåer og ulike stigninger på en tredemølle viste at det er mer variasjon i baner for lavere intensitetsnivåer. Resultatene tyder på at variasjonen, eller mangelen på denne, er av relevans for å estimere energiforbruk.

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1 Introduction

1.1 Background

The World Health Organization estimated that in 2008, over 65 million people were in need of a wheelchair (Borg & Khasnabis, 2008). The use of wheelchairs as the sole mean of mobility has a significant effect on musculoskeletal and cardiovascular function, and there is a high prevalence of obesity, diabetes, and some types of cancer in wheelchair users (Wilby, 2019).

Recently, there has been a focus on investigating the application of multi-sensor devices and activity monitors in manual wheelchair users (MWUs) (Tsang et al., 2016). Most algorithms that predict energy expenditure are based on the able-bodied population, and these generalise poorly to MWUs. Wearable devices have the potential to provide MWUs with informative and motivating feedback that can help them change their physical activity and reduce the risks of chronic disease (Western et al., 2015). The assessment of physical activity and quantification of energy expenditure is inherently more challenging in persons with physical disabilities who use wheelchairs due to altered movement patterns and variations in active muscle mass (Nightingale et al., 2017). These challenges are related to the heterogeneous nature of the wheelchair population, where movement patterns are highly variable due to differential levels or completeness of spinal cord injury.

1.2 The Digital Wheelchair Project

The Digital Wheelchair (DigiW) Project is a cross-sectional research project whose aim is to develop and validate concepts for estimating energy expenditure and physical activity in MWUs (Aakervik, 2019). This project involves various departments from the Norwegian University of Science and Technology, including the Department of Neuroscience and Movement Science and the Department of Engineering Cybernetics.

1.3 Problem Formulation

This study aims to improve the classification of movement intensity by examining correlations between physiological data and measurements from an inertial measurement unit (IMU) during manual wheelchair propulsion. We will focus on cycle classification by analyzing data from an IMU mounted on the wrist, and extracting features from the cycles. The study has two main components:

The first part of the study will focus on extracting the cycle features from the IMU. The features we will be examining here are the average cycle times and the average number of cycles in a 30 second time window. To validate these features, we will also extract the same features from motion-captured trajectories as a reference.

The second part of the study will focus on examining correlations between the cycle features and steady-state energy expenditures. Additionally, we will use the individual cycles to generate an average cycle for multiple 30 second time-windows, then compare cycles between time-windows. Comparing average cycles will allow us to see how the trajectories evolve over time and potentially identify effects of fatigue based on deviations between cycles. The feature we will be examining here is a similarity metric when comparing averaged cycles.

1.4 Similar Studies

This section will present some studies of relevance either to the field of estimating energy expenditure in manual wheelchair users, or studies that have conducted a data collection with similarities to the DigiW project. More information about the data collection in the DigiW project can be found in section 3.

1.4.1 Movement Patterns In Manual Wheelchair Propulsion

Boninger et al., 2002 conducted a study to gather data on the propulsion patterns of manual wheelchair users, with the goal of classifying stroke patterns and determining if different propulsion patterns lead to different biomechanics. The study highlights the fact that manual wheelchair users are at high risk of upper-extremity injury, with repetitive strain injuries causing shoulder pain. The study classifies four different archetypes of stroke patterns, with differences in the recovery phase of propulsion. It concludes that one of the patterns, a semicircular motion, is most advantageous in terms of minimizing the frequency of strokes and reducing the risk of injury.

Slowik et al., 2015 conducted a study collecting kinematic and kinetic data from 170 experienced manual wheelchair users, with the goal of determining the influence of propulsion speed and grade of incline on movement patterns. The study classifies stroke patterns in a similar manner to Boninger et al., 2002. They found that increasing propulsion speed resulted in a shift away from under-rim hand patterns, and that increasing the incline often resulted in an arcing pattern where the hand remains near the handrim throughout the movement cycle.

2 Theory

2.1 Dual Minima Method

The dual minima method is a method commonly used in gait event detection with angular velocity data from a shank-mounted IMU (Allseits et al., 2017). The method is based on exploiting the repetitive nature of human movement, where the two successive minimas within certain parts of the signal is used to classify events in the gait cycle. In this study, we will investigate the potential application of this method for detecting specific points in the propulsion cycle of a manual wheelchair user.

2.2 Procrustes Analysis

Generalized Procrustes analysis is a statistical shape analysis method used to analyze a set of shapes (Gower, 1975). We will focus on ordinary Procrustes analysis, which is a special case of generalized Procrustes analysis where only two shapes are compared. The method takes in a reference shape and a comparison shape and performs a *Procrustes superimposition* on the comparison shape, consisting of rotation, translation, scaling and reflection of the shape in order to produce the best shape-preserving Euclidean transformation from comparison to reference shape (Rohlf, 1999).

2.3 Measures of Performance

2.3.1 Interquartile Range

The interquartile range (IQR) is a statistic measuring the spread of the middle half of a dataset, giving values for the 25th and 75th percentile that holds this data (Rousseeuw & Croux, 1993). The IQR gives an impression of where most of the values in the data lie, with a large range indicating that the central portion of the data is spread out, and a small range indicating a cluster in the central portion. The IQR can be used to determine whether data points are outlier cases by assessing their distance relative to the ranges and the central value (Mowbray et al., 2019).

2.4 Measures of Movement Intensity

There are several metrics for classifying movement intensity, but for this study we will focus on the metabolic equivalent of task.

2.4.1 Metabolic Equivalent of Task

The metabolic equivalent of task (MET) is a metric for the energy expenditure of a person relative to their mass. The metric is relative to the energy expended while sitting at rest, which is quantified as 3.5 mL of oxygen per kilogram per minute (Jetté et al., 1990). To compute the METs metric based on the oxygen consumption of a person, we have the formula $MET = \frac{VO_2}{m \times 3.5}$, where VO_2 is the oxygen consumption in millilitres and m is the body weight of the person in kilograms. Jetté et al., 1990 provides a five-level classification of physical activity based on metrics for energy expenditure, and Table 1 shows the levels based on the METs for men and women.

	Energy expenditure (METs)	
Intensity level	Men	Women
Light	1.6 - 3.9	1.2 - 2.7
Moderate	4.0 - 5.9	2.8 - 4.3
Heavy	6.0 - 7.9	4.4 - 5.9
Very Heavy	8.0 - 9.9	6.0 - 7.5
Unduly heavy	>10.0	>7.6

Table 1: Five-level classification of physical activity based on METs for men and women.

3 Experimental Setup

3.1 Participants

The first part of the dataset consists of data from 20 able-bodied participants as a control group. The second part of the dataset is currently being collected, but will contain data from 20 wheelchair users, therein 10 men and 10 women. In this study, we will only look at data from the control group. The dataset is missing motion-captured trajectories for eight of the participants in the control group, and these have been excluded from this study. Table 2 summarizes personal characteristics of the 12 included participants.

Gender	Number	Age	Body Mass (kg)	Height (cm)	Body mass index (BMI) (kg/m^2)
Male	6	30 ± 6	81.1 ± 8.2	183.8 ± 7.6	24.0 ± 1.7
Female	6	32 ± 10	67.0 ± 9.8	167.7 ± 6.2	23.9 ± 3.3
Total	12	31 ± 8	74.1 ± 11.3	175.8 ± 10.7	23.9 ± 2.5

Table 2: Summary of the characteristics of the included participants.

3.2 Test Protocol

The data is being collected on three separate experiment days, which is scheduled within a three-week span. Each day ranges from rest to high-intensity exercise consisting of wheelchair propulsion a treadmill. The difference between experiment days is the incline of the treadmill, and the order of the experiment days for each participant is counterbalanced. To ensure restitution between experiments, there is a 24 hours minimum grace period between the experiment days. Demographic variables are collected prior to the experiments, including age, body mass, body height, gender and disability-specific characteristics such as type of disability, whether the participant has a spinal cord injury and if so; the injury level and ASIA score (Kirshblum et al., 2011). The participants' physical activity levels are determined by conducting an *International Physical Activity Questionnaire* (IPAQ), resulting in one of the categorical scores "low", "moderate" or "high" (Hagströmer et al., 2006).

The data collection during each experiment day is divided into four parts, except for the 2.5% incline day. An overview can be seen in Figure 1. The first two parts consists of the collection of physiological data during a lying and seated resting period. The third part consists of a five minute warm-up period of wheelchair propulsion on a treadmill where the participant familiarises themselves with the setup. The fourth part is divided into three stages of wheelchair propulsion at different speeds, each four minutes long. Each stage has a specific speed depending on the incline. The incline-speed setup for each day-stage combination can be seen in Table 3. The 2.5% incline experiment day has an incremental test where the treadmill speed is raised incrementally each minute until exhaustion. Data from this test will not be included in this study.

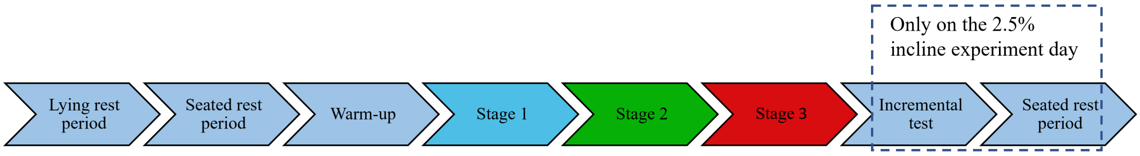


Figure 1: Test protocol for one experiment day.

Incline (%)	Day 1 (0.5)		Day 2 (2.5)		Day 3 (5.0)	
	Men	Women	Men	Women	Men	Women
Stage 1	4	3	3	2	2	1
Stage 2	6	5	4	3	3	2
Stage 3	8	7	5	4	4	3

Table 3: Experimental information describing the incline and speed (km/h) for each day-stage combination.

3.3 Equipment

The following pieces of equipment are used to monitor physical activity during the test days:

- Polar chest strap.
  - Heart rate monitor.
- Inertial measurement unit (IMU)
  - Triaxial accelerometer, gyroscope and magnetometer.
- Vyntus CPX/portable Metamax II (Metamax, n.d.).
  - Measures internal gas exchange, used to compute energy expenditure.
- Wearable: Apple Watch.
  - Gives measurements corresponding to an IMU and a heart rate monitor.
- Qualisys motion capture system (Qualisys, n.d.).
  - Motion trajectories in a 3D space.

3.4 Inertial Measurement Units

There are several IMUs that are used to gather data in each stage. These are placed at different locations on the body; one on the back of the participant, one on the chest, one on the seat of the wheelchair, and one located on the left wrist. The last IMU is part of a wearable smartwatch, and is the only one which will be used for analysis in this study as it captures movement data from the arm. The IMU data is captured during the entire stages with a frequency of 256Hz. In this study, we will only look at the gyroscope part of the IMU data.

3.5 Motion Trajectories

Motion trajectories are captured using the Qualisys motion capture system. The Qualisys data is considered the gold standard in our estimation of the movement, and will be used to check whether the data from the IMU is reliable enough to consistently evaluate movement features. The system captures the motion of markers that are placed on the participants, which can be seen in Figure 2. Additionally, fours markers are placed on the wheelchair, one on the center of each wheel and one on the rim of each wheel. A plot of the trajectories of all markers can be seen in Figure 3a. The Qualisys data is captured twice per four-minute stage, at 1:00 to 1:30, and 2:30 to 3:00 (minute:seconds). These sets of data will be referred to as respectively the first and second Qualisys windows. The Qualisys data is captured with a frequency of 120Hz, and the unit of the data is millimetres.

In this study we will focus on the arm movement, and mostly on the trajectory of the wrist. To reduce complexity in analysis, we will focus on trajectories in two dimensions. Due to comparison with the IMU mounted on the left wrist, we will focus on markers mounted on the left arm. More precisely, the markers we will look at are the LWRL (wrist), LELBL (elbow) and LACR (shoulder) markers. Here, the latter two markers are mainly used for visualizing the movement of the arm. A two-dimensional plot of trajectories from the mentioned markers can be seen in Figure 3b.

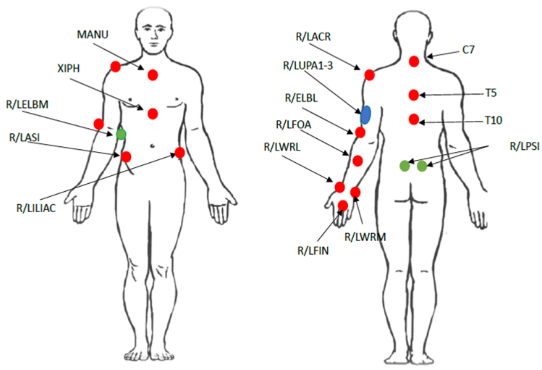
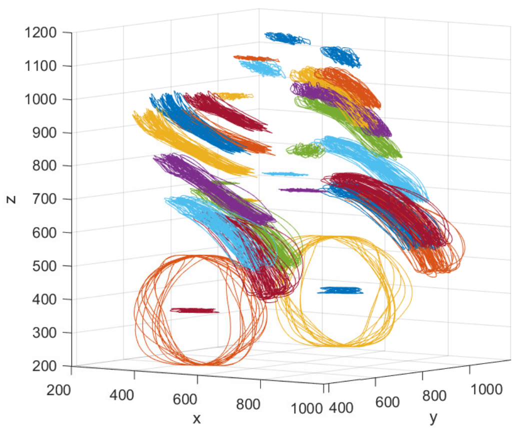
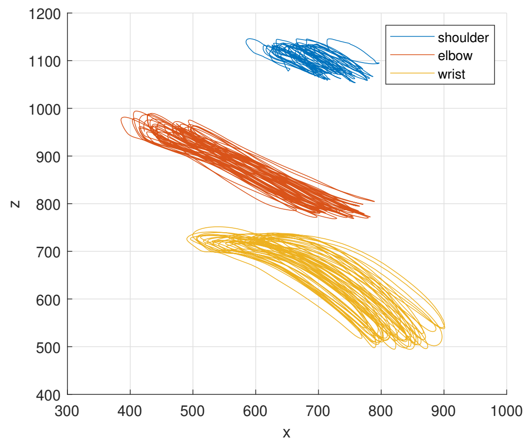


Figure 2: Body markers used in the Qualisys motion capture system.



(a) Qualisys trajectories from all markers.

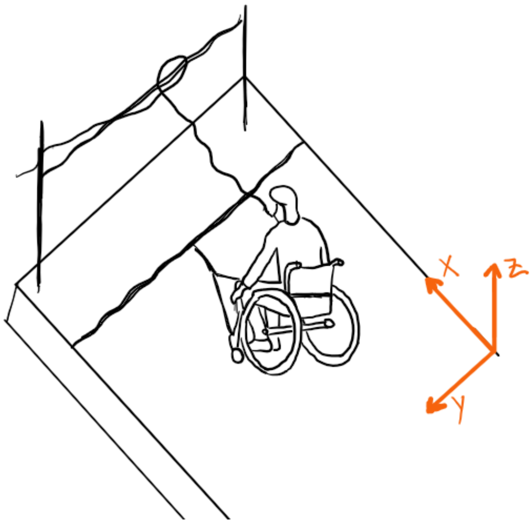


(b) Selected Qualisys trajectories in the XZ-plane.

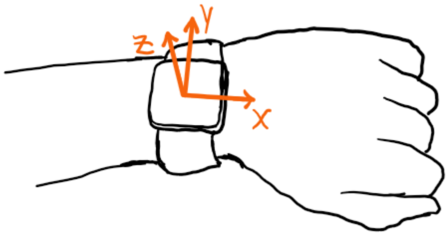
Figure 3: Trajectories from the Qualisys motion capture system.

3.6 Coordinate Frames

One challenge when comparing the Qualisys data and the IMU data is that they have their respective coordinate frames. The coordinate frames can be seen in Figure 4. The Qualisys coordinate frame is static and the position of the markers is measured relative to this. The IMU coordinate frame, however, will both move and rotate with regards to the Qualisys frame. Direct comparison of signals from the IMU to the Qualisys trajectories would require compensating for the rotation. This will not be done in the scope of this study, and we will rather focus on extracting features from the signals and compare these.



(a) Qualisys/treadmill coordinate frame.



(b) Wrist IMU coordinate frame.

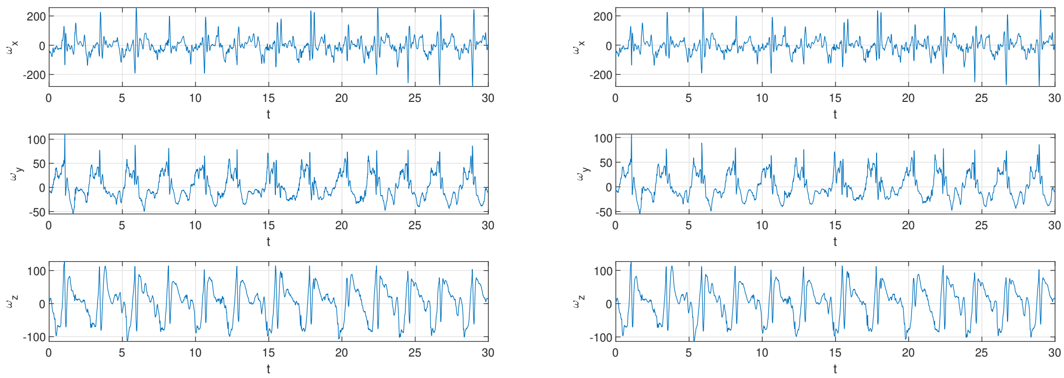
Figure 4: Coordinate frames of treadmill and wrist IMU.

4 Method

This section explains how the data is preprocessed and how various features are extracted from the data. In some cases, the temporal alignment of data from different sources may be offset, which can cause issues when comparing data directly.

4.1 Preprocessing of the IMU Data

In cases when the IMU data is compared to the Qualisys data, the IMU data is downsampled to match the number of samples in the Qualisys data. This means reducing the number of samples by a factor $120/256 \approx 0.469$. This still leaves us with a sampling rate that is much larger than the frequencies of most human movement; Nightingale et al., 2014 mentions that most human movements tend to fall between 0.3 and 3.5 Hz, and that the maximum angular velocities of the forearm in elite wheelchair racers have a frequency component of 3.6 Hz. Figure 5 shows a gyroscope signal in a 30 seconds window before and after being resampled. We can see that the temporal characteristics of the signal is preserved.



(a) Gyroscope signal.

(b) Resampled gyroscope signal.

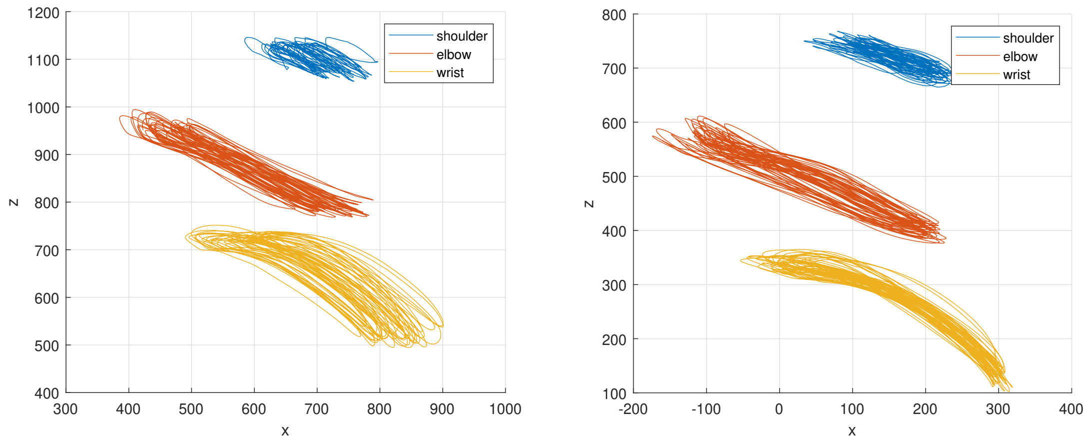
Figure 5: Gyroscope signal before and after resampling.

4.2 Preprocessing of the Qualisys data

As seen in Figure 3b, the cycles in the Qualisys trajectories have some variation in the x-direction, i. e. the direction along the treadmill. As the goal of the analysis is to extract features regarding cycles in the trajectories, this variation is not considered relevant. The variation is compensated for by normalizing the trajectories to the center of the left wheel, subtracting the position of the marker located on the wheel center from the trajectories at each time step. Figure 6 shows the same trajectory as in Figure 3b before and after normalization.

4.3 Steady state energy expenditure

To investigate correlations with energy expenditure, we will often label data based on the steady state energy expenditure of the stage the data is from. We will use an approximation of the steady state energy expenditure, which is calculated using the formula described in section 2.4.1. To approximate the steady state, we remove the final ten seconds of data to remove transient effects, then take the average over the final 60 seconds of the remaining data.



(a) Unnormalized Qualisys trajectories.

(b) Normalized Qualisys trajectories.

Figure 6: Qualisys trajectories before and after normalization to wheel center.

4.4 Extracting Cycle Features

The following two sections describe how cycles are identified from respectively IMU and Qualisys data. For the sake of direct comparison, we only look at the IMU data in the windows where we have Qualisys data as a reference. Both methods are based on the dual minima method described in Section 2.1 and result in an array of extremal points and their timestamps. These are used to extract two features; the number of cycles for the given time window and the length of each cycle in seconds. The number of cycles are given by the number of extremal points minus one, and the length of each cycle is extracted by finding the difference in time between each consecutive pair of points.

4.4.1 Extraction from the IMU Data

To identify cycles, the *findpeaks* algorithm from the *Signal Processing Toolbox* in MATLAB (MathWorks, 2022) was used to detect local minima in the gyroscope data. More precisely, the algorithm detects local maximas, but inverting the signal allow us to detect minimas. The algorithm lets you among other things specify a lower threshold for the maxima and a minimum distance between them.

One of the main issues with this approach is that the amplitude of the gyroscope signals varies both between participants and between day-stage combinations, usually in the range $[-200, -50]$ (degrees/second). This makes selection of the threshold for detecting minima complicated, as the aim is to find a method that generalizes across participants. This led to a trade-off where individual thresholds would give better performance in detecting correct minimas, but requires manual inspection. For simplicity, it was chosen to use a single threshold for all participants. After trial and error with data from different participants and day-stage combinations, a threshold of -40 degrees/second and a minimum distance of 0.65 seconds between minimas was chosen.

Another issue was deciding which of the gyroscope axes to use for classifying minima, or whether to use a combination of all of them. For simplicity, it was decided to focus on data from a single axis, choosing the axis based on the distribution of the minima using the Qualisys data as a reference. The IQR was computed for the data points from each axis to estimate the spread of the minimas along the trajectory. The axis that had the tightest spread between the 75th and 25th percentile in both the X and Z direction of the treadmill coordinate system (weighed equally), was chosen. The thought behind using this metric rather than simply variance is to make the method more robust to outliers, for instance if the method produced a tight spread of points but with some misclassifications that would skew other statistics.

Given that most of the movement in the Qualisys trajectory of the wrist is in the X-direction of the Qualisys frame, it was hypothesised that the Y-axis of the gyroscope would be favoured. This is due to the Y-axis of the gyroscope being approximately parallel to the ground and thus the treadmill when the participant holds their arm straight down. See Figure 4 for reference.

4.4.2 Extraction from the Qualisys Data

As one might guess, the identification of cycles became easier when extracting them directly from the Qualisys data. To minimize the possibility of having multiple extremal points within the same cycle, it was chosen to use maxima in the X-direction of the Qualisys coordinate system to classify cycles. The same *findpeaks* algorithm was used, with a lower threshold of zero to force the algorithm to ignore the minimas.

4.5 Averaging Over Cycles

An initial idea for extracting cycles purely from the IMU data was to combine information from the accelerometer and the gyroscope signals, seeing if the trajectories from the Qualisys system could be reproduced from these. However, this approach came with problems both concerning comparing trajectories in different coordinate systems and due to the noisy nature of accelerometer signals. The first problem could be solved by doing a rotation of the trajectories, for instance by utilizing tools from Procrustes analysis to compare between trajectories from the IMU and the Qualisys system. However, the second problem made for a bigger issue; this method involved double-integration of the accelerometer signal to get the trajectories. Without dedicating much time to deal with the noise, the measurement drift and the gravity components in the accelerometer signal, the integrals would either blow up or produce drifting trajectories. To reduce complexity, it was instead chosen to use information from the gyroscope to split the Qualisys trajectories into cycles.

The following method is used for cycles extracted both from the gyroscope data and the Qualisys data:

First, we need to extract the cycles from the Qualisys data and decide on a length for the average cycle. Having identified the gyroscope minimas in the IMU case, or the maximas in the X-direction of the wrist trajectory in the Qualisys case, these are used to slice the Qualisys data into cycles. To define the length of the average cycle, the median cycle length is used. This is done in order to make the method more robust to misclassified extremal points, for instance if the method misses a cycle or two. If the mean of cycle lengths were to be used, a misclassification could potentially lead to a skewed average length, leading to poor performance. Second, we need to make all the extracted cycles have the same length in order to generate an average. This is done by interpolating the cycles to have the length of the median. Finally, the average cycle is generated by taking an average over all cycles at each time step.

Some of the flaws with this method is that it assumes that all cycles have approximately the same start and end points, and that each classified cycle contains only one cycle.

4.6 Procrustes Distance

The Procrustes transform was used to compare average cycles within the same experiment day. To compute the transform, the *procrustes* function from the *Statistics and Machine Learning Toolbox* in MATLAB was used. This function also returns the Procrustes distance, which is a measure of dissimilarity between the shapes. This measure is the sum of squared differences between corresponding points in reference and comparison shape, standardized by the scale of the reference shape. This results in a measure in the range $[0, 1]$, where higher values means a more dissimilar shape.

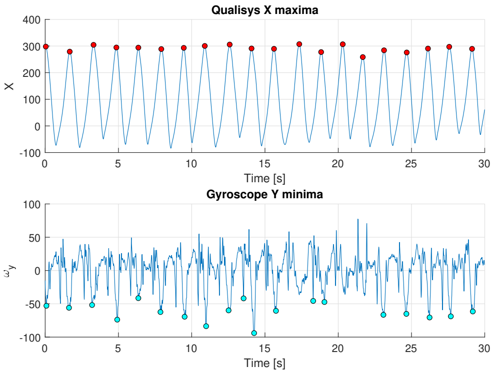
4.7 Comparing Procrustes Distances and Energy Expenditure

To investigate possible correlation between the Procrustes distances and steady state energy expenditure we will focus on data extracted from the second Qualisys window of the first and the last stages. The focus on the second Qualisys windows is due the fact that these are closer to the end of the stage, and the energy expenditure will be approximating the steady state. Comparing data from the first to the last stage allow us to see whether the hand movement patterns changes over time, and if so, see if this is correlated with an increase in energy expenditure.

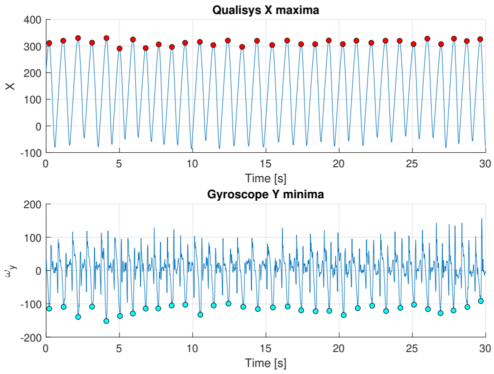
5 Results

5.1 Cycle Features

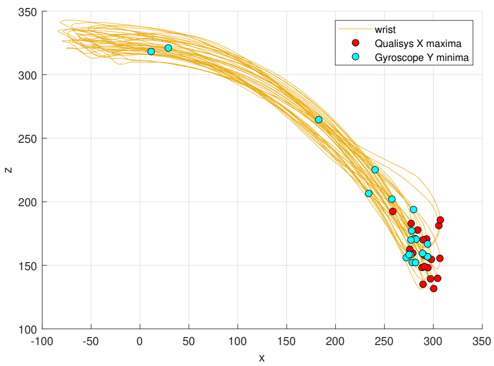
Figure 7 shows signals from the Qualisys system and the gyroscope for one participant for the first and the third stage of the third experiment day (5 % incline). The top subfigures show extracted extremal points for both sets of data, and the lower subfigures show the same extremal points plotted on the trajectory of the wrist. The gyroscope signal in the first stage is more erratic than in the third, and the method fails to extract minima for some seconds after about 19 seconds. Here, the method also identifies multiple minima within a single cycle, which is the likely cause of the outliers seen in Figure 7c. For the third stage, the method seems to correctly identify all minima and thus cycles, which is supported by the clustering seen in Figure 7d.



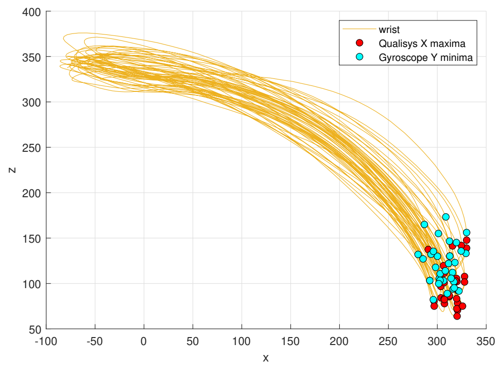
(a) Day 3, stage 1.



(b) Day 3, stage 3.



(c) Day 3, stage 1.

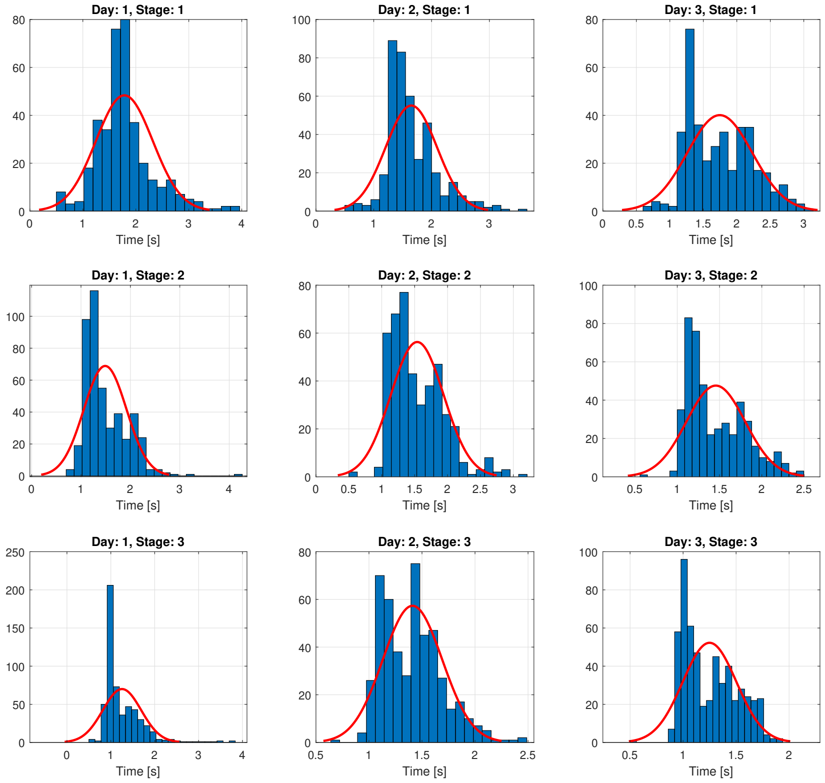


(d) Day 3, stage 3.

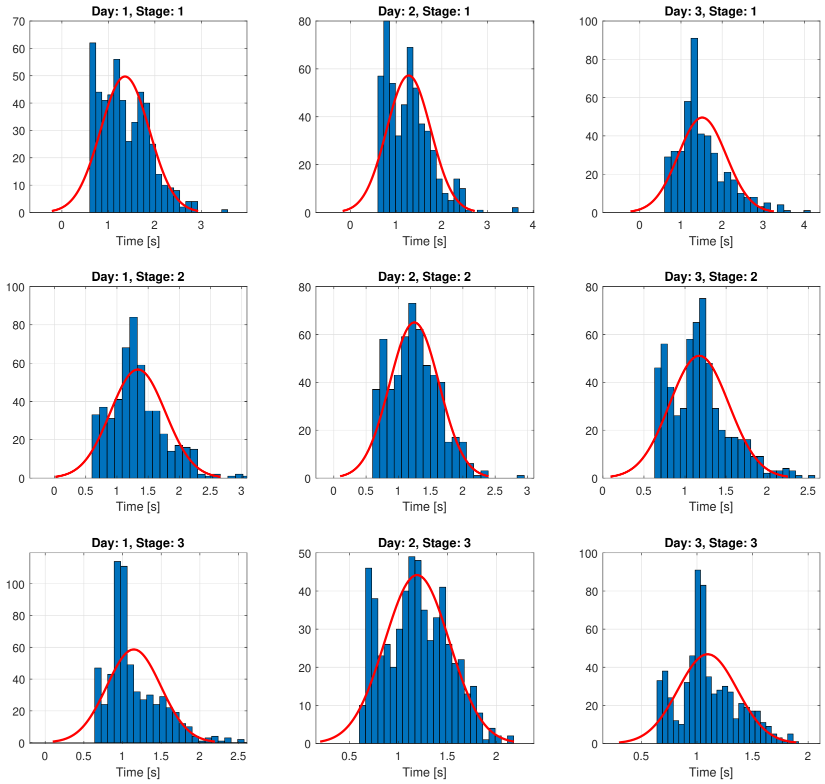
Figure 7: Comparison of motion signals with extracted extremal points.

5.1.1 Cycle times

Figure 8 shows cycle times for all participants extracted from both Qualisys and gyroscope data plotted as histograms for each day-stage combination. Each histogram contain cycle times from both Qualisys windows for all 12 participants. A normal distribution has been fitted to each histogram, and values for the means (μ) and standard deviations (σ) can be seen in Table 4. A general trend seems to be that the method used on the gyroscope data underestimates the cycle times, with smaller differences for the higher stages.



(a) Cycle times from Qualisys data.



(b) Cycle times from gyroscope data.

Figure 8: Histograms of cycle times with a fitted normal distribution.

	Day 1				Day 2				Day 3			
Equipment	Qualisys		Gyroscope		Qualisys		Gyroscope		Qualisys		Gyroscope	
Parameters	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Stage 1	1.78	0.54	1.36	0.53	1.65	0.44	1.28	0.48	1.75	0.49	1.52	0.58
Stage 2	1.49	0.43	1.34	0.44	1.54	0.40	1.25	0.38	1.46	0.35	1.17	0.36
Stage 3	1.26	0.44	1.15	0.35	1.41	0.28	1.19	0.33	1.25	0.25	1.10	0.27

Table 4: Parameter estimates after fitting a normal distribution to the cycle times from Qualisys and gyroscope data.

5.1.2 Number of cycles

Similarly to what was done with cycle times, Figure 9 shows histograms of the extracted number of cycles for all participants from Qualisys and gyroscope data for each day-stage combination. A normal distribution has been fitted to the histograms, resulting in parameters shown in Table 5. We have only 24 samples (12 from each Qualisys window of the stage) for each histogram, resulting in more coarse shapes when comparing to the histograms of cycle times. The trend here is that the gyroscope data gives a higher number of cycles than the Qualisys data.

	Day 1				Day 2				Day 3			
Equipment	Qualisys		Gyroscope		Qualisys		Gyroscope		Qualisys		Gyroscope	
Parameters	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Stage 1	15.7	4.2	21.1	5.3	17.0	4.3	22.5	6.9	16.0	4.5	18.7	4.3
Stage 2	19.2	4.8	21.5	4.1	18.3	4.6	23.2	4.6	19.6	4.3	24.5	4.9
Stage 3	22.9	6.7	25.5	5.3	20.0	4.2	24.1	4.4	23.1	4.7	26.5	3.6

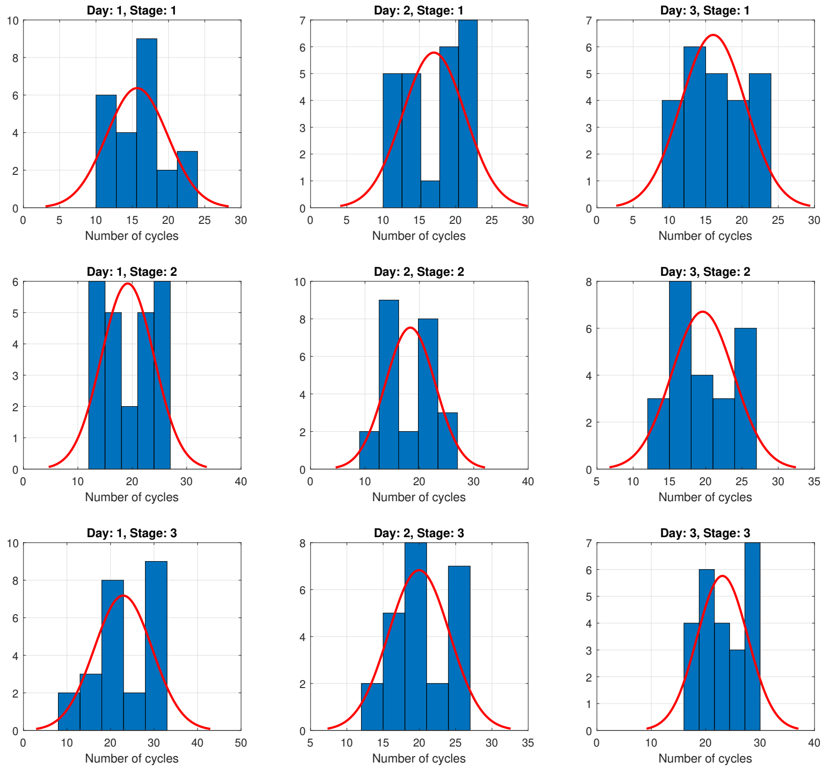
Table 5: Parameter estimates after fitting a normal distribution to the number of cycles from Qualisys and gyroscope data.

5.1.3 Comparing Qualisys and IMU Features

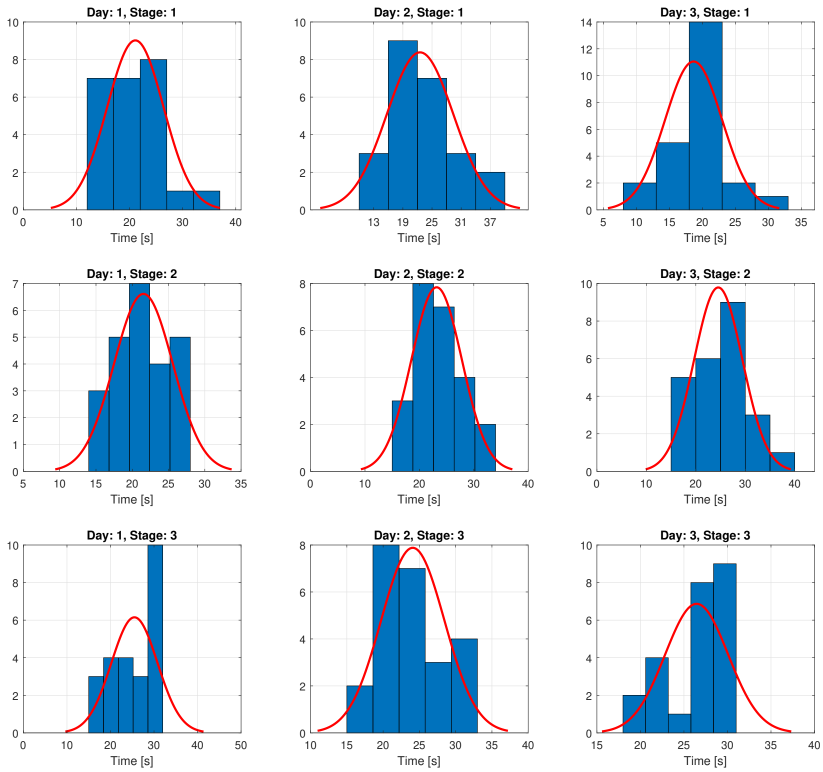
Figure 10 shows scatter plots of the average values of the extracted features from each data source for each day-stage combination. A reference line representing perfect positive correlation has been added to each plot. To check for clusters based on either physiological measurements or demographic info about the participants, the same scatter plots is shown labeled by different information. Figure 10a shows the features labeled with the intensity levels given by the METs ranges shown in Table 1. The points seems to be closer to the reference line as the intensity increases. Figure 10b shows the features labeled with the categorical scores resulting from the IPAQ questionnaire, with no clear clusters. Figure 10c shows the features labeled by the gender of the participant, also with no clear clusters. Figure 10d shows the features labeled by the age of the participant. Here, the points seem to indicate closer correlation between the data sources as the age of the participant increases.

5.1.4 Which Gyroscope Axis Was Favoured?

Table 6 shows the gyroscope axis that was chosen for identifying minima for each Qualisys window based on the method and IQR criteria described in section 4.4.1. Unlike hypothesized, each axis was chosen approximately the same number of times, with a slight favour towards the Z-axis.

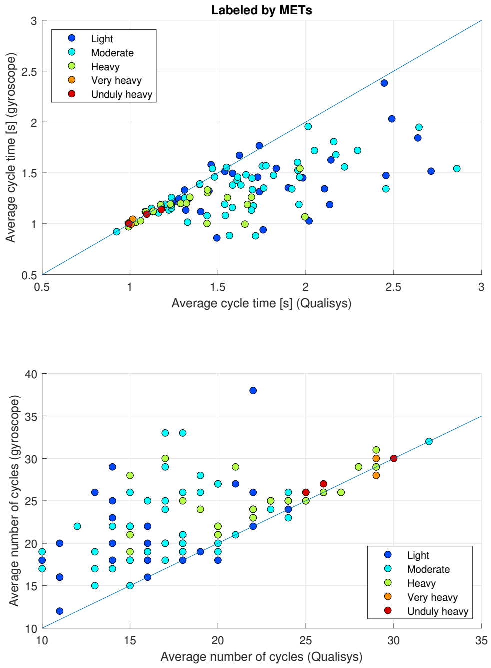


(a) Number of cycles from Qualisys data.

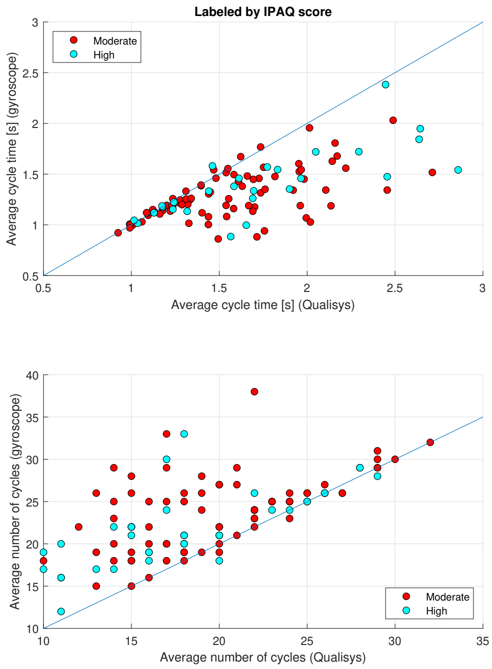


(b) Number of cycles from gyroscope data.

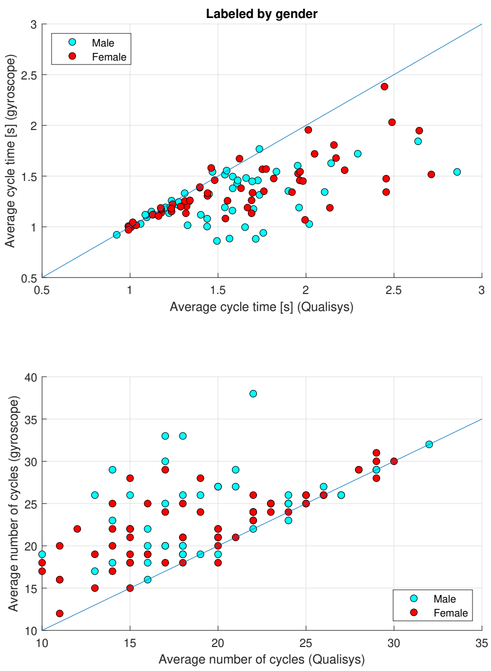
Figure 9: Histograms of number of cycles with a fitted normal distribution.



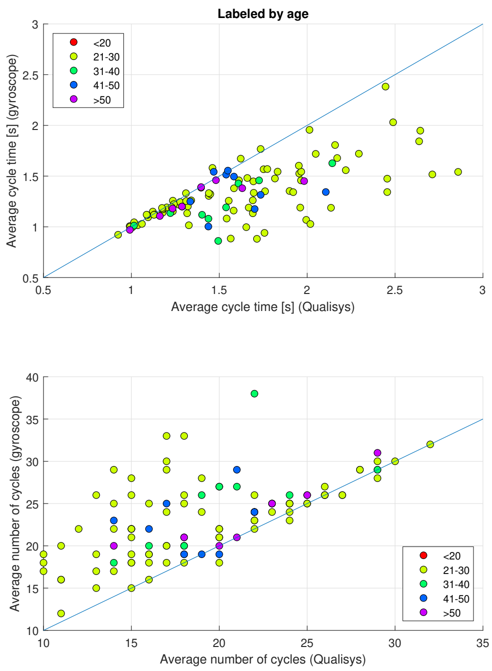
(a) Labeled by intensity level.



(b) Labeled by IPAQ score.



(c) Labeled by gender.



(d) Labeled by age.

Figure 10: Scatter plots of average cycle times and average number of cycles, plotting Qualisys- and IMU features against each other.

Gyroscope axis	Times chosen
X	65
Y	73
Z	78

Table 6: Number of times each gyroscope axis gave the least spread of data based on the IQR criteria.

5.1.5 Correlation Between Cycle Features and Energy Expenditure

Figures referenced in this section are made with features extracted from the Qualisys data. Analysis using features from the gyroscope data support the same observations made, but for the sake of conserving space, the Qualisys features are used.

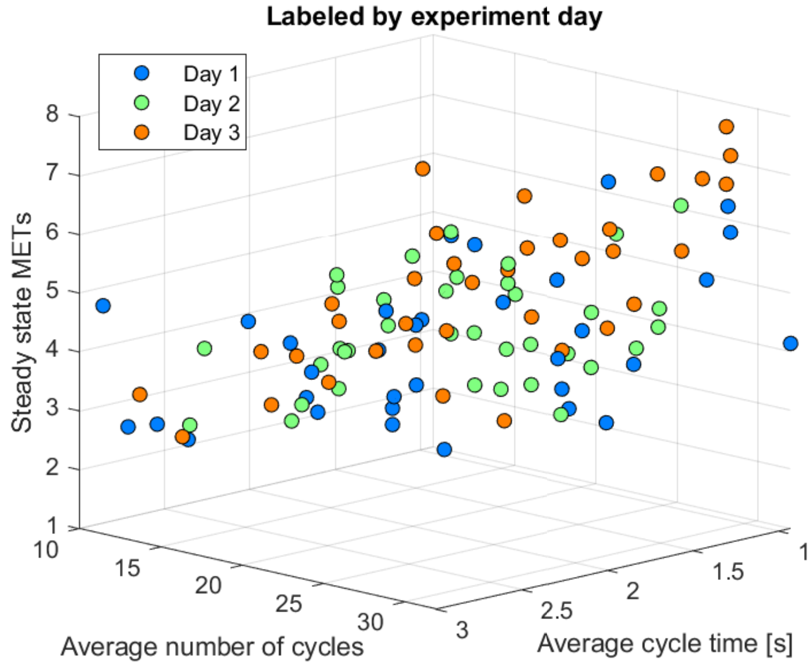
Figures 11a and 12a show three-dimensional scatter plots of the cycle features and the steady state energy expenditure based on the METs metric. Figures 11b and 12b show only the cycle features. Points in Figure 11 is labeled by the experiment day that the data used to generate the features came from, and there's no clear clusters in the points. By labeling by the stage however, Figure 12 shows a trend that the lower stages tends to have less cycles and a higher cycle time, and that the highest stages generally have more cycles and a lower cycle time. Points from the first and second stages are more spread out compared to the third stage. The correlation between energy expenditure and cycle times are more clear for the second and third stage, especially in the areas where the cycle time is less than 1.5 seconds. We can see from the 2D scatter plots that the cycle features are anticorrelated, meaning that a high average number of cycles implies a low average cycle time, and that a high average cycle time implies a low average number of cycles. The steady state energy expenditure is generally higher for the higher stages, implying that the features can be relevant in predicting energy expenditure.

5.2 Cycle Averages

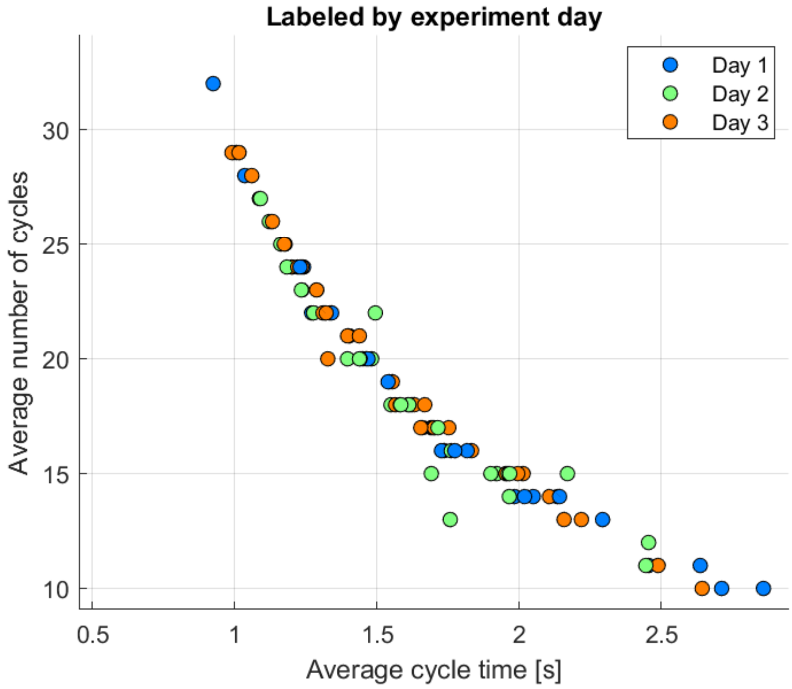
Figures 13 and 14 show the resulting wrist trajectories for the same participant when averaging over cycles using extremal points respectively from the gyroscope- and the Qualisys data. By comparing the figures, we can see that the gyroscope produces trajectories that in some cases match those of the Qualisys data, while in other cases failing completely. A cause of this may be that the data is not correctly aligned in time, or that the gyroscope produces minimas that are too spread out along the trajectories to produce a correct average. Other factors may be measurement noise and biases in the IMU. These may vary from day to day, making a method intended to generalize hard without compensating for these factors.

The Procrustes distances in the gyroscope case are very high, even in cases such as in the lower left and lower right of Figure 13, where visual inspection implies that the shapes are indeed similar. The cause of this may be that even though the method produces "correct" averages, it chooses a different gyroscope axis to produce the average for each of the Qualisys windows. When comparing cycles we assume that they have approximately the same start and ending points, which may not be the case here as minimas from different axes can relate to different points along the trajectories.

Figure 15 show resulting trajectories from another participant using the Qualisys data to average over cycles. Here, we can see that the trajectories from the third experiment day has a pattern that is dissimilar to the other experiment days. Not all participants showed the same trend, but this instance supports the observations in Slowik et al., 2015, where increasing incline often resulted in an arcing pattern.

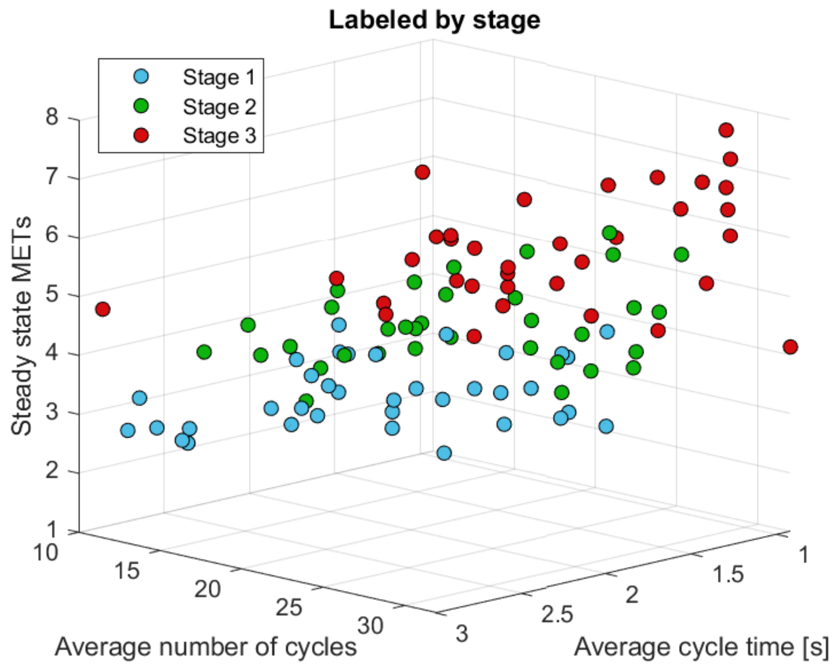


(a) Scatter plot of cycle times, number of cycles and steady state METs.

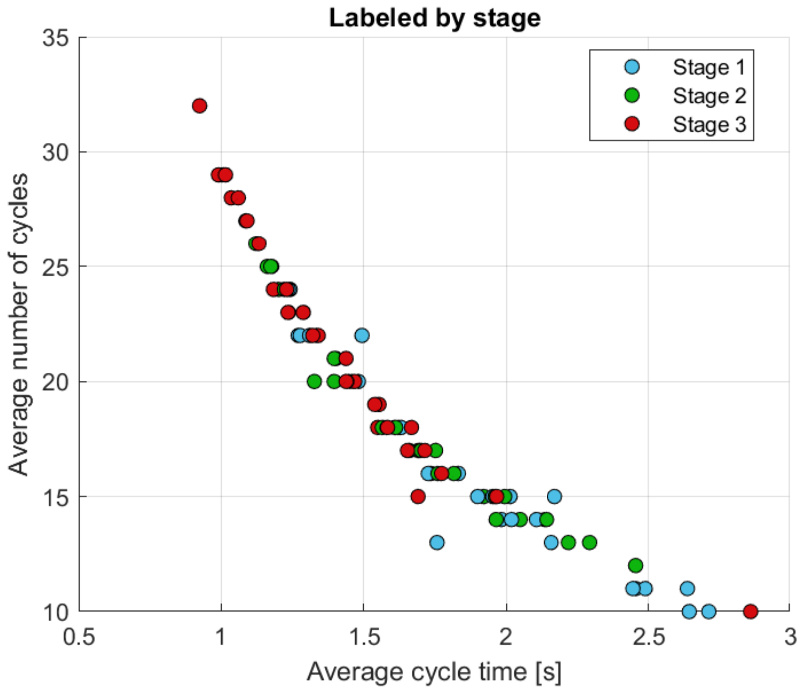


(b) Scatter plot of cycle times and number of cycles.

Figure 11: Scatter plots labeled by experiment day.



(a) Scatter plot of cycle times, number of cycles and steady state METs.



(b) Scatter plot of cycle times and number of cycles.

Figure 12: Scatter plots labeled by stage.

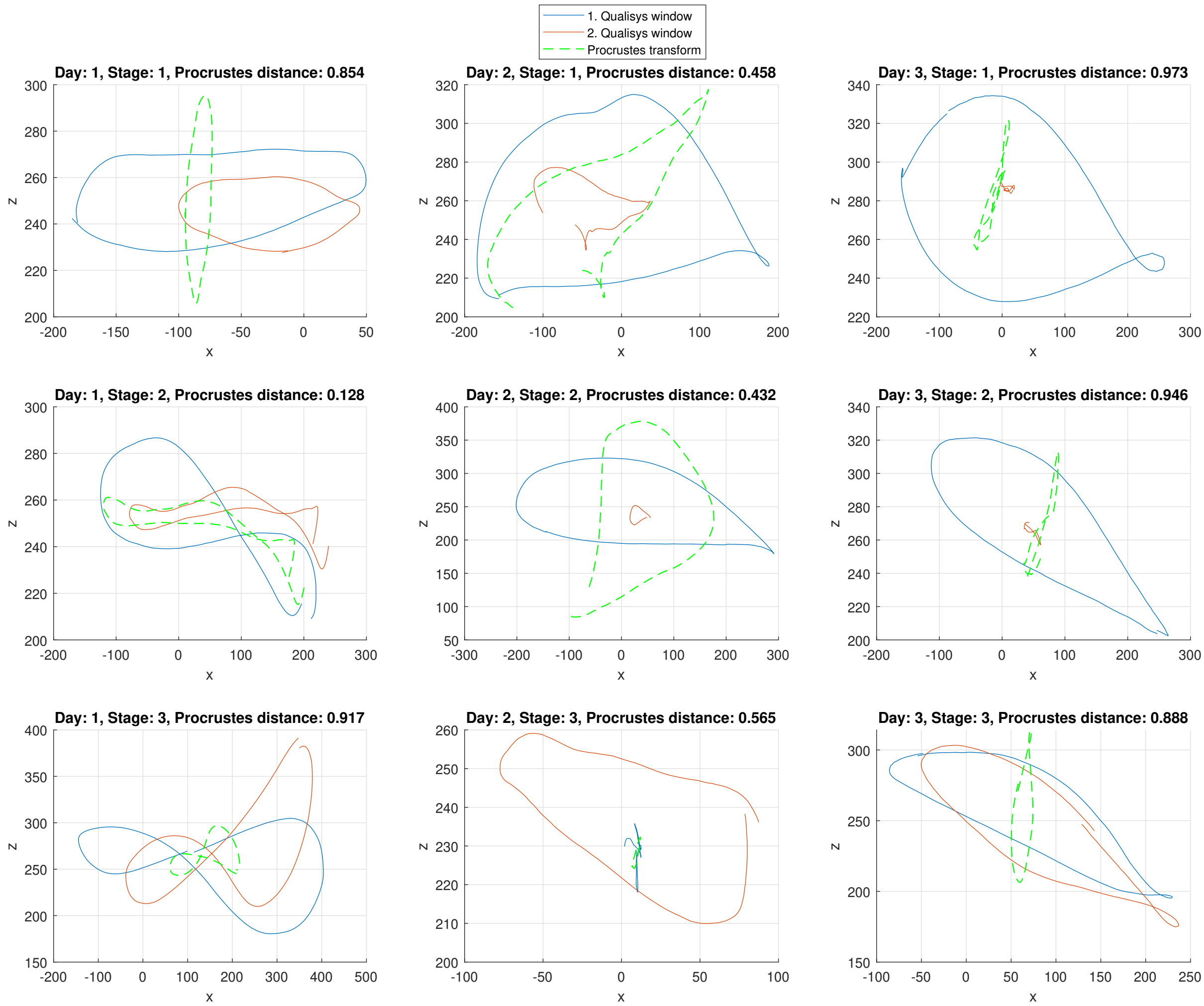


Figure 13: Average wrist trajectories from the Qualisys windows and the Procrustes transform between them. The averages are made using minima from the gyroscope signal in the Qualisys windows to split the Qualisys wrist trajectory into cycles.

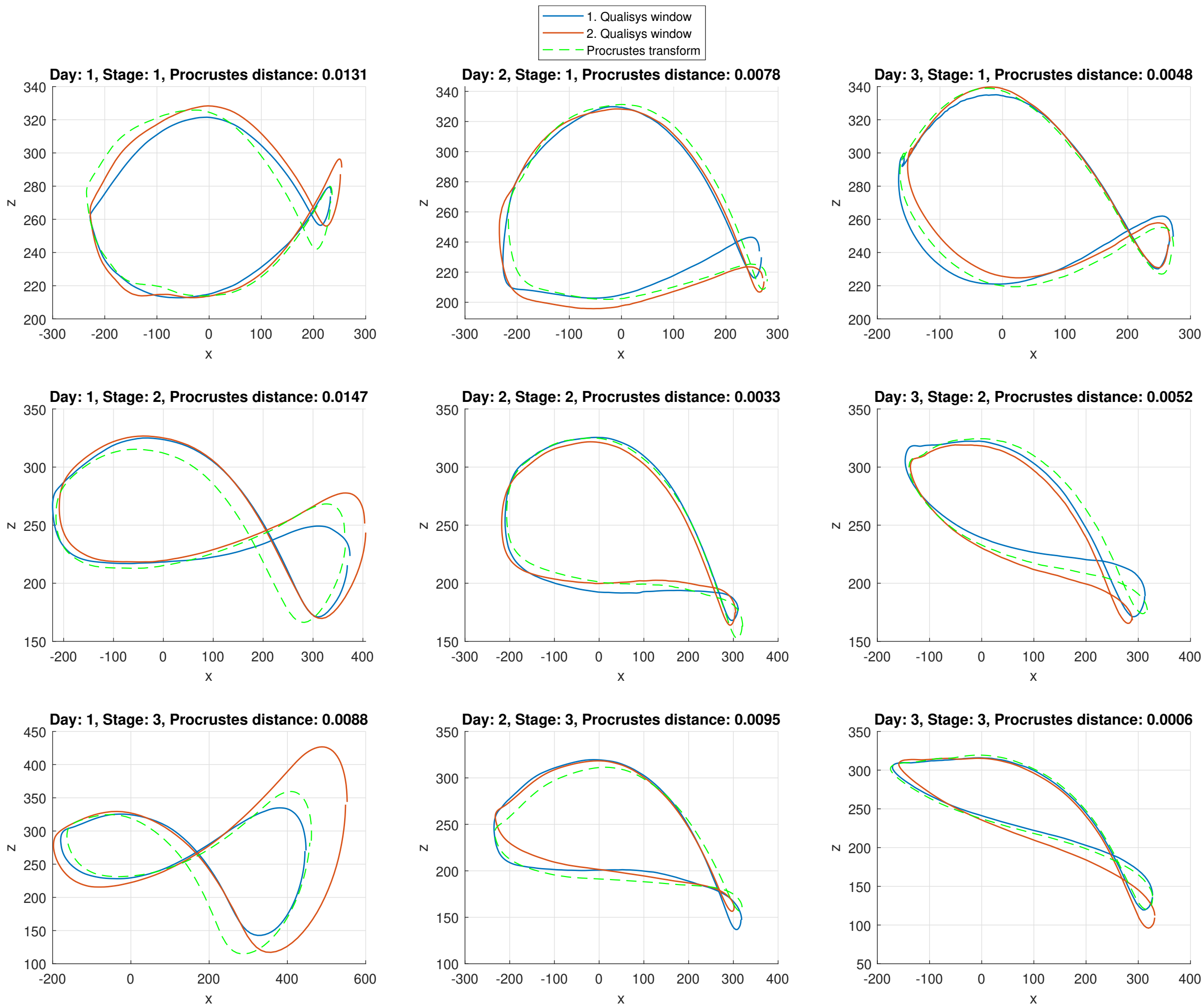


Figure 14: Average wrist trajectories from the Qualisys windows and the Procrustes transform between them, made using Qualisys data. The data is from the same participant as in Figure 13.

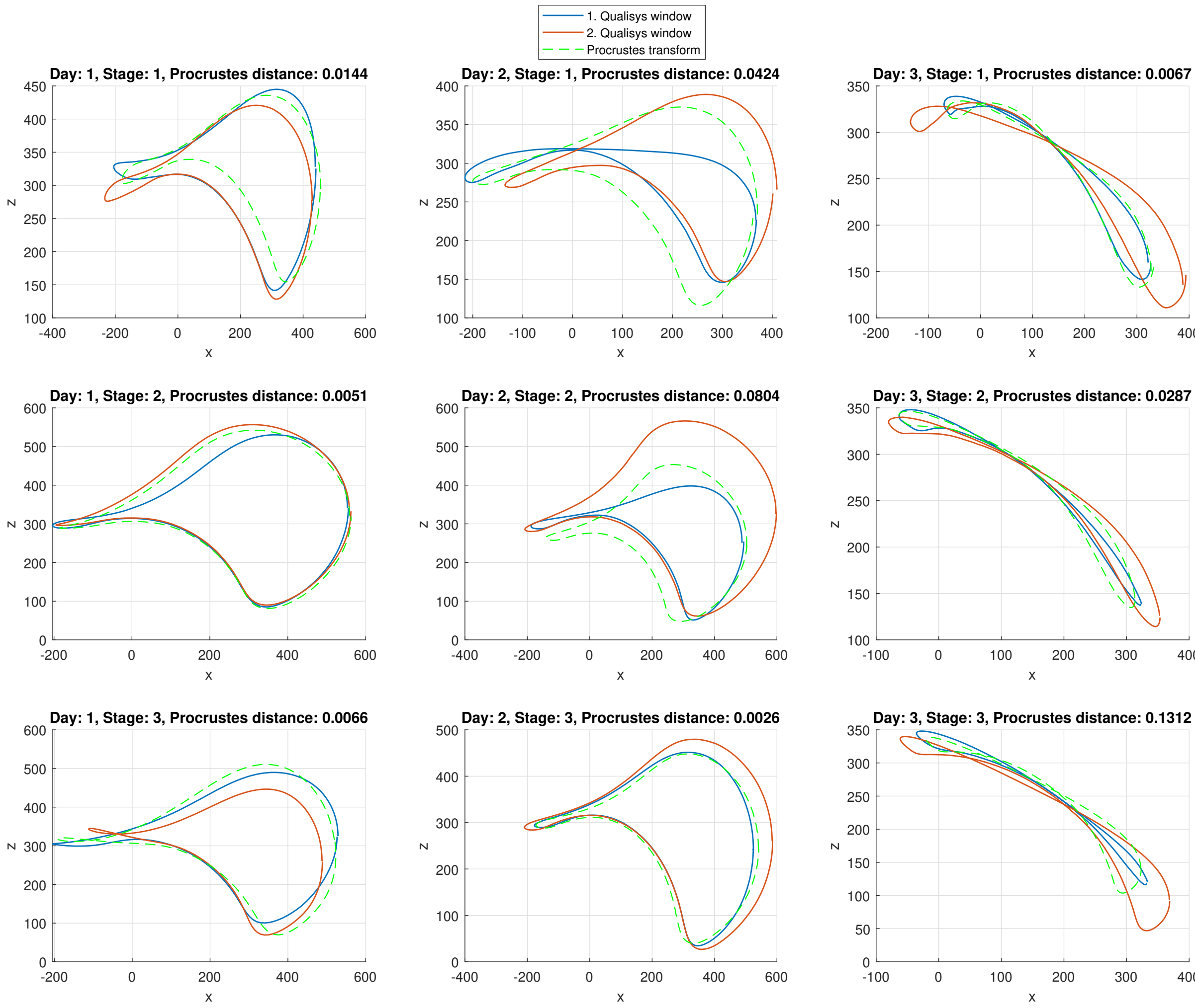


Figure 15: Average wrist trajectories from the Qualisys windows and the Procrustes transform between them, made using Qualisys data.

5.2.1 Procrustes Distances

Due to the issues when performing Procrustes analysis using the gyroscope data, further results regarding Procrustes distances are from using only the Qualisys data.

To investigate whether the movement pattern changes within a stage, the Procrustes distance was calculated based on the average cycles generated from the first and second Qualisys window. Table 7 shows the resulting Procrustes distances. The distances takes on the same trend for each experiment day, with a higher value for the first stage than the others. This seems to indicate that there is less variability in the movement patterns when there is a higher physical demand. Another interesting observation is that the Procrustes distances are lower for the second stage for each experiment day compared to the first and the third stage. The mechanism behind this is unclear, but it implies that there is some nonlinearity in the Procrustes distances depending on the speed.

	Average Procrustes distance		
	Day 1	Day 2	Day 3
Stage 1	0.0388	0.0809	0.1069
Stage 2	0.0223	0.0305	0.0163
Stage 3	0.0351	0.0482	0.0250

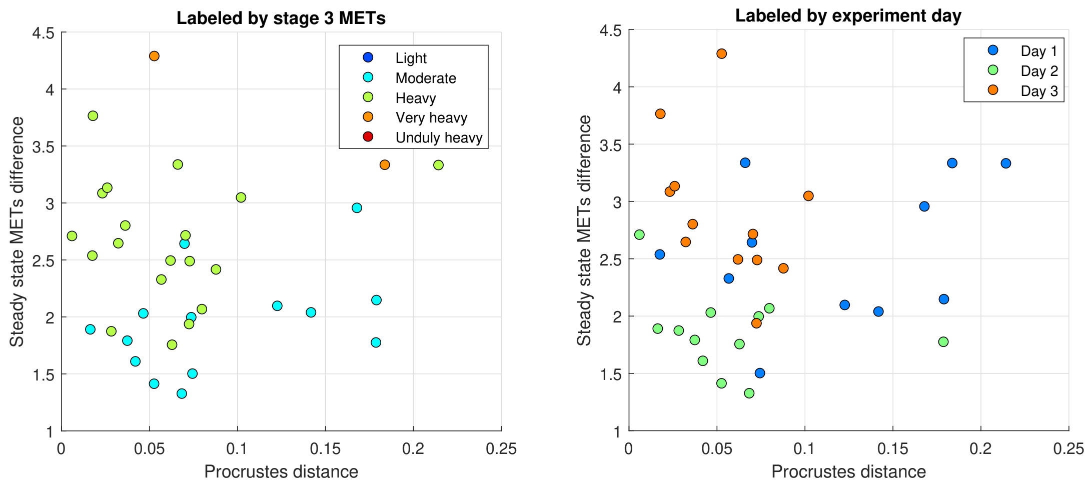
Table 7: Average intra-stage Procrustes distances from comparing average cycles between Qualisys windows (within stages).

5.2.2 Correlation Between Procrustes Distances and Energy Expenditure

Using the method described in section 4.7, Figure 16 shows Procrustes distances between the averages from the first and the third stages plotted against the differences in steady state energy expenditure. Points in Figure 16a are labeled with the intensity level from the third stage. This plot implies that there is a positive correlation between the intensity level and the difference in energy expenditure. Points in Figure 16b are labeled with the experiment day the data is from. This plot show more signs of clusters, with higher Procrustes distances in the data from the first experiment day. None of the plots show a direct connection between the Procrustes distances and the difference in energy expenditure. Table 8 shows the average inter-stage Procrustes distances for each experiment day, implying that there is more variability between trajectories from the first day.

	Day 1	Day 2	Day 3
Procrustes distance	0.1441	0.0577	0.0546

Table 8: Average inter-stage Procrustes distances from comparing average cycles from the third to the first stage (within experiment days).



(a) Labeled by intensity level from stage 3.

(b) Labeled by experiment day.

Figure 16: Scatter plots of Procrustes distances and difference in METs, comparing data from the third stage to data from the first stage.

6 Discussion

6.1 Validity of the IMU Data

To extract the cycle features from the gyroscope, the current method relies on distinct minimas. This works well for the stages with higher speeds on the treadmill, which results in gyroscope signals with a more clear structure and of higher amplitudes. For the low-speed stages however, the method doesn't perform as good. Table 4 showed a relatively wide gap between the distribution of mean cycle times from each data source in the first stage, especially for the first two experiment days. The gap is smaller in the third experiment day, possibly due to the higher incline leading to a higher physical demand for the participant, leading to a more clear signal structure. The gap between the mean cycle times becomes smaller for the second and third stages, implying that the features from the gyroscope approximates the reference features from the Qualisys system as the intensity increases. This is further supported by Figure 10a which shows that the points labeled with higher intensity lies closer to the reference line, meaning there is a closer correlation between the gyroscope and Qualisys data for higher intensity activities.

6.2 Correlations with Energy Expenditure

Of the features extracted in this study, the average cycle times and average number of cycles shows correlation to the energy expenditure. As shown in section 5.1.5, the two features are anticorrelated. Figure 12 shows that low average cycle times and high average number of cycles becomes more prevalent in the higher stages, where the energy expenditure generally is higher. We observed that the correlation between the cycle features and energy expenditure is more clear for the second and third stage. This can be explained by the increasing physical demand as the treadmill speed is higher for these stages. Higher speeds leads to faster movement which leads to more cycles. Including both of these features in a model predicting energy expenditure might prove redundant due to the strong anticorrelation, but the results show that using at least one of them can be useful in such a model.

Table 7 shows that the Procrustes distances generally were higher in the first stage compared to the other stages. The low Procrustes distance in the second and third stages imply that trajectories from these stages has less variability. Combined with information from other sources, this feature might be relevant in the prediction of energy expenditure as it can aid in classifying the intensity of the activity. However, the participants included in this study are not experienced wheelchair users, so the variability may be due to the participants' lack of experience with wheelchair propulsion.

In section 5.2.2 we showed that there was no clear relation between the Procrustes distances and the difference in energy expenditures when comparing between the first and third stages. However, Figure 16b and Table 8 shows a trend that the inter-stage Procrustes distances are higher for the first experiment day than for the others. The cause of this may be that the low speed relative to the incline in the first stage of the first experiment day allowed the participants more freedom of movement than for higher speeds.

6.3 Correlations Between Cycle Features and Demographic Variables

In Figure 10 (b-d), we examined the relation between the cycle features from each data source and a selection of demographic variables. There were no clear connection between either the IPAQ score or the gender of the participant and the correlation between the data sources. However, labeling the features by age seemed to indicate a stronger correlation between the data sources with higher age of the participant. This was especially clear for participants above the age of 50, less so for participants in the range of 41 to 50 years. However, these ranges only have a single participant in each of them, and therefore it is not clear whether the increase in correlation is due to the age of the participants. Nine of the twelve participants included in this study fall in the range of 21 to 30 years, meaning that we should expect to see a bigger spread of data in this range. We would need more data from participants in the higher ranges to investigate further.

Another possible reason for the increase in correlation between data sources based on the age demographic may be due to the movement pattern of the participants.

6.4 Methodological Considerations

The *findpeaks* method used to implement the dual minima method is very rigid. To make the method generalize across both participants and different day-stage combinations, a threshold of -40 [deg/s] and a minimum cycle time of 0.65 [s] had to be specified. A better alternative could have been to make an adaptive solution using a windowing function, having an adaptive threshold based on the structure of the gyroscope signal in the given window.

The implemented method to compute Procrustes transforms relies on data from the Qualisys system, and not the IMU. Capturing motion trajectories using a similar setup is not viable in an every-day setting, so if the Procrustes distances were to be used in an activity tracker we would need to extract the information from a different data source. This might be possible using a sensor fusion approach to combine data from the different measurements of the IMU.

The study was limited to a selection of participants from the control group. Most of the participants included were in the range of 21 to 30 years, and none of them fell within the "low" IPAQ category. The demographics might not properly reflect the population of MWUs, so an increased study size may improve the design.

6.5 Future work

The objectives of this study was to investigate correlations between features extracted from movement data and energy expenditure, and to investigate the validity of extracting these features from a wrist-mounted IMU.

Future work should aim to replicate our findings with a larger sample size, and with greater demographic diversity. Performing the same analyses on the MWU part of the dataset should be done to see if we can generalize results from the control group to the MWUs. This would also allow us to see whether the variability observed in the first stage is due to lack of experience in wheelchair use for the control group, or if the variability is due to more freedom of movement for lower intensity physical activity.

To improve the validity of the IMU for lower intensity activities, a more advanced technique than the dual minima method should be considered.

In section 5.2.1 we observed that there was a nonlinear connection between the Procrustes distance within stages and the speed of the treadmill, where the second stage showed the least variability in movement patterns. More data should be collected to investigate the cause of this, perhaps with more incremental treadmill speeds to see how the variability of the trajectories change with speed.

Another interesting approach would be to classify the movement pattern of the participant for each day-stage combination, for instance based on the four patterns presented in Boninger et al., 2002, then to see the prevalence of features based on the stroke pattern. Perhaps some patterns give more easily identifiable features?

A group of students from the Department of Engineering Cybernetics, including myself, will later combine experiences from working on the study towards creating a virtual reality exercise rig for MWUs based on an omnidirectional treadmill.

7 Conclusion

In this study, we have investigated the validity of using a wrist-mounted IMU to classify cycles, and to extract information from said cycles during manual wheelchair propulsion. Using the dual minima method, the validity of features from the IMU increases with the intensity level. Demographic variables provided no clear connection to the validity of the data. For lower intensity levels, more precise methods of classifying cycles can increase the performance.

It was shown to be a correlation between the average cycle time, the average number of cycles and the energy expenditure for a given time-window. Lower cycle times was found to correlate to a higher amount of cycles and higher energy expenditure.

A method for generating average cycles and comparing them between given time-windows was demonstrated. The data suggests that there is more variability in hand movement patterns for lower intensity activities. For the first experiment day, with 0.5% incline, it was shown to be more variability in movement patterns between stages than for experiment days with higher inclines.

Further research should investigate the application of using these features in predicting energy expenditure.

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