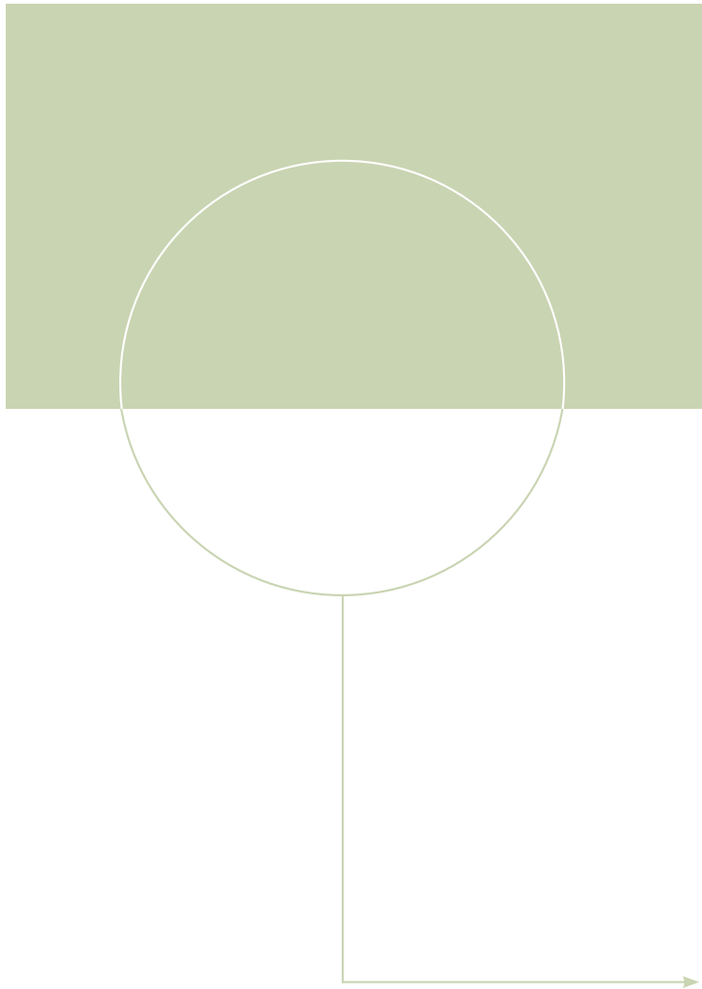

Master's thesis

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Estimation of lactate concentration during excercise

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Master of Science in Cybernetics and Robotics
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Abstract

This thesis explores the development and implementation of models and estimation of continuous lactate concentration in athletes during exercise. The goal of such a estimator is to accurately and reliably determine the lactate concentration of an athlete. When exercising it is important to keep the intensity under control, which can be done by measuring the lactate concentration in the blood intermittently during exercise. This requires expensive equipment and discomfort as a small blood sample is taken. To make lactate concentration a more widely accessible physiological marker, a cheaper, less intrusive method of estimating the lactate concentration is sought in this thesis.

To generate the data required for such an estimator, test protocols where designed and two test subjects went through the same set of testing days. The data was gathered, synchronised and organized for further use. A model based on physiological principals was chosen and simplified for use in a Kalman filter estimator. The Matlab implementation of this estimator yielded limited results as the data basis was not that large. A larger study with a larger data basis might yield results that are more applicable on other athletes.

Chapter 1 describes the motivation behind the problem, as well as the given problem description and approach. Chapter 2 introduces the essential theoretical background for the methods described in Chapter 3. Chapter 4 contains all the results from both the data gathering process as well as estimations with different inputs. In Chapter 5 these results are discussed and summarized.

Denne avhandlingen utforsker utviklingen of implementering av modeller og estimering av kontinuerlig laktat konsentrasjon hos utøvere under trening. Målet med en slik estimator er å bestemme laktakkonsentrasjonen hos en utøver. Når man trener er det viktig og styre intesiteten, dette kan gjøres ved å måle laktatkonsentrasjonen i blodet underveis i treningen. Dette krever dyrst utstyr og er ubehagelig å gjennomfør siden det kreves en blodprøve. For å gjøre intensitetstyring etter laktat mer tilgjengelig for folk søkes det derfor etter en billigere, mindre invasiv metode for å estimere laktatkonsentrasjonen under trening.

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Chapter 1

Introduction

1.1 Motivation

Blood lactate concentration is a key parameter in determining athletic performance in long distance endurance sports. Especially the lactate threshold has been linked to athletic performance [3]. Blood lactate measuring devices are expensive and uncomfortable to use, and they do not provide a continuous measurement while exercising. Thus, a cheaper, more accessible method for continuously estimating blood lactate values is desirable.

In the term project pursued during Fall 2020, the student aimed to estimate blood lactate level by using a variety of sensors and physiological measurements collected from athletes doing high-intensity exercise. The data sources included heart rate, VO2 and external power, but the lactate level was measured quite seldom and only after completion of each part of the activity.

1.2 Objective

In this project, the student will gather a data set where lactate was sampled at a higher rate and further study methods for continuously estimating blood lactate level by exploiting information from sensors with the following distinct/dissimilar characteristics:

- Sensors with relatively high sampling rates, used to measure a state with quite rapid dynamics (e.g., measurements of external power).
- Sensors with relatively high sampling rates, used to measure a state with rather slow dynamics (e.g., a heart rate monitor).
- Sensors with relatively low sampling rates, used to measure a state with more rapid dynamics (e.g., VO2 and blood lactate measurements sampled every 30s-5min).

- Sensors with a low sampling rate and measuring over large windows and an inaccurate scale (e.g., RPE, "rate of perceived effort").

The data set to be gathered will be collected in a laboratory setting, while being closely monitored. In this environment, many of the relevant physiological parameters can be measured. To make the blood lactate estimates more useful in regular training settings and more accessible for the public, the student will also investigate model reduction strategies, and the utilization of cheap and readily available sensors.

Specifically, the student will perform the following tasks:

1. Literature review on methods for exploiting data from sensors with very different dynamics, sampling rates and drift. Specifically, describe the Kalman filter and its applications in sensor fusion, interpolation and smoothing.

2. Design test protocols and gather the data set, including methods for organizing the data (calibration, synchronization etc.).

3. Find and apply suitable methods for integrating the data from the various sensors and estimate blood lactate level.

4. Compare and evaluate the results of the various models or methods applied on the data set.

1.3 Approach

To solve the given objective an examination of previous literature of similar applications in estimating physiological sizes is the first step. Then for gathering of physiological data tests will have to be designed and tested before the real recordings can begin. Then based on the result of these findings design a model based on the findings that will serve a starting point for further exploration. Lastly the models must be evaluated and compared on part of the gathered data.

Chapter 2

Theory

2.1 Lactate production

2.1.1 Physiology

To perform any action, the cells which make up our bodies, needs energy. Energy is released from a compound called adenosine triphosphate (ATP). Only a small amount of ATP can be stored in a skeletal muscle cell at any given time and thus there is a need for constant replenishing. To produce ATP the body has three main energy systems. For short lasting intense efforts, ATP stored in the muscle is utilized in combination with breaking down phosphocreatine (PCr). These are called the ATP-PCR system and is not required to have oxygen present to produce energy. For activity lasting longer than approximately 8 s, there is also a large contribution of energy from the process of breaking down glycogen to lactate. When the effort is longer than about 1 min, oxidative phosphorylation generates the majority of ATP [5].

During easy exercise the energy demand is met through oxidative sources. For exercise with enough intensity the energy demand may exceed the energy which the muscle cells is able to produce by oxidative means, thus ATP is sourced from the breakdown of glucose and glycogen where the endpoint of the reaction chain is pyruvate. If the muscle cells are lacking oxygen, i.e. anaerobic, pyruvate is reduced to lactate [7]. This is the main source of lactate into the plasma. To clear lactate from the plasma the lactate is mainly oxidized in muscle cells, or liver to be reused as an energy source. For sub-maximal exercise lactate is cleared at a similar rate as it is produced, leading to a steady state of lactate concentration in the blood. However, at intensities above the lactate threshold blood lactate will begin to accumulate [13].

2.1.2 Modelling

Academic interest in modelling the kinetics of lactate production and removal dates back to the beginning of the 20th century. In 1936 the rate of lactate acid removal

during exercise was established to be proportional to the concentration present at the time [12]. In 1981 Freund and colleagues published a two-compartment model [16]. The model is an application of mass conservation law and has a compartment for the working muscle as well as the rest of the lactate space. Blood lactate concentration is then expressed for each compartment by the following differential equation

$$V\dot{La} = PR - REX - MRR + LU - LR \tag{2.1}$$

Where V is the volume, La is the lactate concentration, PR is the production rate, REX is the excretion, MRR is metabolic removal rate, LU is uptake from other compartments and LR is release to other compartments.
In a paper released in 2002, Alois Mader among other things, built out the idea of a two compartment model even further. Lactate concentration was described in a two compartment model as the following

$$\dot{La}_m = -K_1(La_m - La_b) + 1.35(v_{La,ss,pH} - v_{La,ox,m}) \tag{2.2}$$

$$\dot{La}_b = V_{rel}(K_1(La_m - La_b) - v_{La,ox,b}) \tag{2.3}$$

Where La_m and La_b is the concentration in the muscle compartment and blood compartment respectively, V_rel is a constant describing the relative volume between active muscles and blood, typically between 30-50%[9]. K_1 describes the rate of exchange between the two compartments leading to a lower exchange rate as the lactate concentration increases.

$$K_1 = 0.065La_b^{-1.4}$$

Furthermore, what drives the model is the description of the production and consumption rate, $v_{la,ss,pH}$ and $v_{la,ox}$. The rate of production is scaled from the known maximum rate of production based on current work rate. The oxidative consumption is mostly determined by the current expenditure of VO_2. We are left with a two compartment model which describes at what rate lactate is accumulated in the muscle compartment and exchanged into the blood compartment.

Understanding of lactate progressively increased during the later 20th century and by the turn of the century lactate was attributed other roles than just being the dead end of glycolysis [4]. In 2012 Moxnes and Sandbakk published a mathematical model of lactate production and removal [11]. The model is a second order differential equation for two compartments, much like previously mentioned models by Freund. It was originally constructed for use in cross country skiing, however it has been adapted for use in cycling as well [15].

$$\dot{C}_m(t) = (\frac{V}{V_m})[p_0 D(\bar{\bar{Q}}_a(t) - d_0\frac{Tanh(\chi C_m(t))}{\chi}D(Q_a(t))(Q_{max} - Q_a(t))] - k_{1a}\frac{C_m(t) - C_b(t)}{V_m} \tag{2.4}$$

$$\dot{C}_b(t) = k_{1a}\frac{C_m(t) - C_b(t)}{V_b} \tag{2.5}$$

Where symbols are explained in Table 2.1

Table 2.1: Symbols used in Equation 2.1.2

C_m	Blood lactate concentration in the muscle.
C_b	Blood lactate concentration in the blood.
V_m	Volume of the muscles.
V_b	Volume of blood.
V	Sum of V_b and V_m.
p_0	Rate of pyruvate disappearance due to oxidation.
$D(Q_a(t)$	Function relating aerobic to rate of lactate disappearance.
d_0	Parameter scaling the rate of lactate disappearance.
χ	Parameter describing saturation of lactate disappearance rate.
Q_{max}	Maximal aerobic power.
k_{1a}	Parameter scaling the exchange between compartments.

The model was fitted quite well to experimental data, having uncertainty of less than $\pm$ 0.5 mmol/L during varying sub-maximal exercise intensities [11]. The benefit of models like this is that parameters used in the model will have a physiological interpretation. These parameters does however need to be adjusted to every new activity type and athlete.

2.2 RPE

The Borg Rating of Perceived Exertion (RPE) was introduced by Gunnar Borg in 1998 as a tool for measuring physical activity intensity level [2]. The tool is used by asking a participant how heard they feel their body is working. The idea is that the body is able to accurately measure it's own work rate based on sensations such as heart rate, respiration, sweating and muscle fatigue. Originally the scale went from six up to twenty to mimic the approximate heart rate during exercise ($\sim$ 60-200 BPM), however a scale from one to ten is also commonly used.

2.3 Kalman filtering

2.3.1 Background

The Kalman filter has it's name from the Austrian Mathematician R.E Kalman who in 1960 published a paper on a recursive solution of the problem of linear filtering of discrete data[8]. Since then, the solution has been researched and applied heavily, especially in the fields of autonomous navigation. The Kalman filter itself consists of a set of mathematical equations which efficiently computes the solution of a least-squares problem. The filter provides an estimation of every time step along the way as well as a dynamically updated estimate of the uncertainty of the estimation. Today the estimation technique sees use in many different applications ranging from economics, weather forecasting to estimation of blood glucose concentration[14].

Mathematically we can describe the problem as the following

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{2.6}$$
$$y_k = C^\intercal x_k + v_k \tag{2.7}$$

where the random variables w_k and v_k describes the noise in the process and measurement. These variables are assumed independent from each other, white, and distributed normally according to the following

$$p(w) \sim N(0, Q) \tag{2.8}$$
$$p(v) \sim N(0, R). \tag{2.9}$$

If x is a n-dimensional state space vector ,y is a m-dimensional measurement vector and u is a l-dimensional input vector then A is a $n \times n$ matrix and B is a $n \times l$ matrix which together describes how the state moves forward one time step given some input, u. $C^\intercal$ is a $m \times n$ matrix that relates the state and measurement, y.

Let $\bar{x}_k$ be the a priori estimate of the state at time k. This is based on our last a posteriori estimate, $\hat{x}_{k-1}$ propagated through the process model to produce the a priori estimate for the next time step. If we define the estimation error as

$$\bar{e}_k = x_k - \bar{x}_k \tag{2.10}$$
$$\hat{e}_k = x_k - \hat{x}_k, \tag{2.11}$$

then the a priori error covariance, $\bar{P}_k$, is

$$\bar{P}_k = E[\bar{e}_k \bar{e}_k^\intercal] \tag{2.12}$$

and similarly the a posteriori error covariance, $\hat{P}_k$, is

$$\hat{P}_k = E[\hat{e}_k \hat{e}_k^\intercal]. \tag{2.13}$$

Now we want an a posteriori state estimated as a linear combination between the a priori state estimate $\hat{x}_k$ and the actual measurement y_k. We get the following

$$\hat{x}_k = \bar{x}_k + K(y_k - C^\intercal \bar{x}_k) \tag{2.14}$$

where K is called the Kalman gain which we which to establish with minimizing $\hat{P}_k$, the a posteriori error covariance. By substituting Equation 2.14 into Equation 2.11 and then into Equation 2.13 we can take the derivative of the trace of $\hat{P}_k$ with regards to K and by setting this equal to zero we arrive at the following

$$K_k = \bar{P}_k C (C^\intercal \bar{P}_k C + R_k)^{-1} \tag{2.15}$$

To illustrate the effect of the measurement covariance, R_k and a priori error covariance, $\hat{P}_k$ on the Kalman gain we look at the limits as these go to towards zero

$$\lim_{R_k \to 0} K_k = C^{\intercal -1} \tag{2.16}$$
$$\lim_{\hat{P}_k \to 0} K_k = 0 \tag{2.17}$$

Table 2.2: Prediction step equations.

$$\boxed{\bar{x}_{k+1} = A\hat{x}_k + Bu_k}$$

$$\boxed{\bar{P}_{k+1} = AP_kA^\intercal + Q_k}$$

Table 2.3: Correction step equations.

$$\boxed{K_k = \bar{P}_kC(C^\intercal \bar{P}_kC + R_k)^{-1}}$$

$$\boxed{\hat{x}_k = \bar{x}_k + K(y_k - C^\intercal \bar{x}_k)}$$

$$\boxed{\hat{P}_k = (I - K_kC^\intercal)\bar{P}_k}$$

In the case of Equation 2.16 then Equation 2.14 will remain with only y_k as the estimate since we assume there is no uncertainty in the measurement value and thus the estimate should be equal to the measurement. However in the case of Equation 2.17 then Equation 2.14 will be equal to the a priori estimate $\bar{x}_k$ as we assume there is no uncertainty in the a priori estimate and thus there is no need for the more uncertain measurement with variance R_k. To implement the Kalman filter we need to formulate these calculations as an algorithm. We separate the calculations into two steps, one which uses the underlying model of the process to predict the state of the next time step based on the current estimate. The equations can be found in Table 2.2.

The other step is to correct the estimate whenever there is a measurement available. Here we calculate the Kalman gain using Equation 2.15 and update our a posteriori estimate and error covariance. The equations can be found in Table 2.3. If there is no measurement available, no correction step is needed and the a posteriori estimates are just equal to the a priori estimates.

Chapter 3

Method

3.1 Experimental data gathering

3.1.1 Subjects

Two recreationally trained subjects as listed in Table 3.1 are recruited to gather data.

Table 3.1: Subjects for data gathering.

	Subject A	Subject B
Gender	Male	Female
Age	23	24
Weight	79	65
AT	270	160

3.1.2 Equipment

All tests were preformed on an indoor bike ergometer (Concept2, Morrisville, United States). Before data gathering the bike ergometer was calibrated using inbuilt software. Blood lactate levels were measured using a handheld lactate test meter, Lactate Pro2 LT-1730 (ArkRay Inc, Kyoto, Japan), by taking 5 μL blood samples from the fingertips. Heart rate data was recorded using a heart rate monitor (Polar H7, Polar Electro, Kempele, Finland) connected to a watch.

3.1.3 Testing protocols

Before each day subjects are asked to train lightly in the 24 hours leading up to the session. Before commencing on the session a standardized warm up of ten minutes at a low effort (approximately at half of AT) is done. In each test the subjects are blinded to the blood lactate measurements to not interfere with the RPE given.

3.1.4 Anaerobic threshold

The test procedure consists of a 10 minute warm up before an incremental ramp of five minutes where after each stage the blood lactate is measured and power is increased by 20 Watt. This is repeated until a value of 1.5 mmol/l above the resting lactate concentration values is reached. The power achieved at this stage was then recorded for further use and denoted as the anaerobic threshold.

3.1.5 Day 1

Blood lactate levels are sampled with one minute intervals, whereas the RPE is sampled after each interval.

3.1.6 Day 2

Blood lactate levels are sampled with a varying interval in the following pattern, at 0, 2, 4, 5, 6 and 7 minutes after the start of each interval, whereas the RPE is sampled after each interval.

3.1.7 Day 3

On day three the subjects does a continuous effort of 14 minutes with varying intensity. The blood lactate levels, as well as RPE, is sampled with one minute intervals.

Table 3.2: Data gathering sessions.

Day	1	2	3
Number of intervals	10	3	1
Length of intervals [min]	2	6	14
Intensity [% of AT]	110	90	Varying
Length of break[min]	1	2	0

3.2 Lactate kinetics modelling

3.2.1 Overview

The goal of the model is to take the external output of the athlete measured on the bike and produce a continuous estimation of the lactate concentration in the blood compartment. The measurements used to correct the estimation is taken by blood samples from the finger and thus is from the blood lactate compartment.

Table 3.3: Constants used in Equation 3.2, Equation 3.3 and Equation 3.4.

Constant	Value
τ_{vo2}	0.60
K_1	2
V_{rel}	0.35

3.2.2 Continuous model

To continuously estimate the lactate concentration of the athlete a Kalman filter is used. The underlying process of lactate concentration is modelled as follows. Let x be the state space vector, then

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} La_m \\ La_b \\ VO2 \end{bmatrix} \tag{3.1}$$

We have three states which if we differentiate we have

$$\dot{La_m} = -K_1(La_m - La_b) + (v_{la,ss} - v_{la,ox,m}) \tag{3.2}$$

$$\dot{La_b} = V_{\text{rel}}(K_1(La_m - La_b) - v_{la,ox,b}) \tag{3.3}$$

$$\dot{VO2} = \frac{\tilde{VO2} - VO2}{\tau_{vo2}} \tag{3.4}$$

where

$$v_{la,ox} = K_2 VO2 \tag{3.5}$$

$$v_{la,ox,m} = \frac{2}{3} v_{la,ox} \tag{3.6}$$

$$v_{la,ox,b} = \frac{1}{3} v_{la,ox} \tag{3.7}$$

Let u be the input vector, then

$$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} v_{la,ss} \\ \tilde{VO2} \end{bmatrix} \tag{3.8}$$

$v_{la,ss}$ is a constant, K_3 multiplied by the external power at that time step, and $\tilde{VO2}$ is the oxygen consumption rate that the athlete will stabilize at some time given an intensity. Thus we can formulate it on the form

$$\dot{x} = Ax + Bu$$

where

$$A = \begin{bmatrix} -K_1 & K1 & \frac{-2K_2}{3} \\ K_1 V_{\text{rel}} & -K_1 V_{\text{rel}} & \frac{-1K_2 V_{\text{rel}}}{3} \\ 0 & 0 & \frac{-1}{\tau_{vo2}} \end{bmatrix} \tag{3.9}$$

$$B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & \frac{1}{\tau_{vo2}} \end{bmatrix} \tag{3.10}$$

Table 3.4: Standard deviation in measurement with Lactate Pro 2. All sizes given in mmol/l.

Range	Standard Deviation
0-1.9	.06
2.0-4.9	.11
5-0-9.9	.22
10.0-14.9	.52
15+	.60

The measurement y is the concentration of lactate in the blood compartment, La_b.

$$y = C^\intercal x \tag{3.11}$$

$$C^\intercal = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \tag{3.12}$$

For further use in a discrete Kalman filter the model is discretized using a time step of one second.

3.2.3 Measurement covariance

To determine the covariance of the measurements values from a study of handheld lactate measuring devices [1] gave the values give in Table 3.4 for the standard deviation for the Lactate Pro 2. Thus the covaraiance, R_k, can be determined dependently on the value of the measurement, y_k.

3.2.4 Process noise

The covariance matrix, Q, is kept diagonal and subject to tuning to increase performance of the Kalman filter.

3.2.5 Tuneable constants

To adjust the model between subjects two variables, K_3 and K_4, is set to values that minimizes the mean square error between the estimate and measurement at the time of the measurement. Specifically the fminsearch from the optimization toolbox in MATLAB [10]. The two variables where minimized using data points from the first two days of testing.

3.2.6 Outlier removal

When a measurement is more than two standard deviations away from the estimate it is considered an outlier and the correction step of the Kalman filter is skipped for that iteration.

3.2.7 Implementation

The Kalman Filter was implemented in MATLAB[10]

Chapter 4

Results

4.1 Data gathering

For all figures, red dots is measured lactate concentration given in mmol/l and black line is power given in watts.

Anaerobic threshold

The results from the anaerobic threshold test is summarized in Table 4.1 and Table 4.2.

4.1.1 Day one intervals

Figure 4.1 shows the results from day one of data gathering.

Table 4.3: Subject A's RPE at Time minutes after start of day one.

Time	6	14	22
RPE	6	6	7

Table 4.4: Subject B's RPE at Time minutes after start of day one.

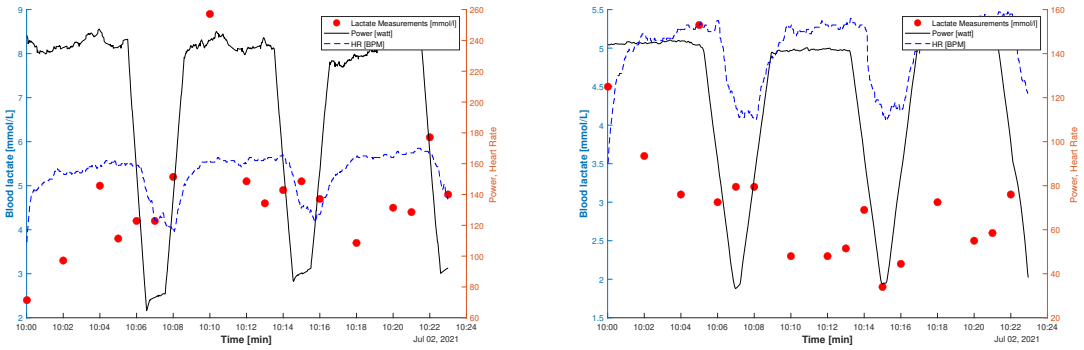
Time	6	14	22
RPE	5	6	6

Table 4.1: Values of blood lactate concentration after ended stage at indicated power for subject A.

Power[watt]	190	210	230	250	270
Lactate concentration[mmol/l]	1.4	2.3	2.4	3.0	3.9

Table 4.2: Values of blood lactate concentration after ended stage at indicated power for subject B.

Power[watt]	140	160	180
Lactate concentration[mmol/l]	2.2	4.1	12.5



(a) Subject A.

(b) Subject B.

Figure 4.1: Day one intervals. Power, Heart Rate and blood lactate measurements are plotted.

4.1.2 Day two intervals

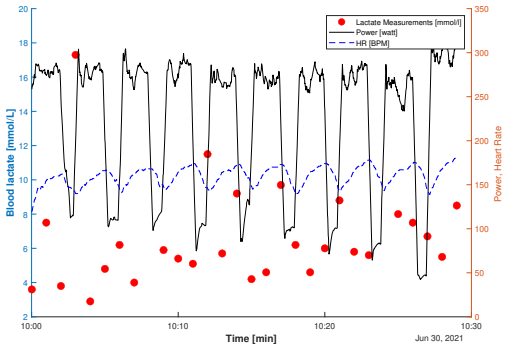
Figure 4.2 shows the results from day two of data gathering. Unfortunately the first half of subjects B's test day was lost to data corruption.

Table 4.5: Subject A's RPE at Time minutes after start of day two.

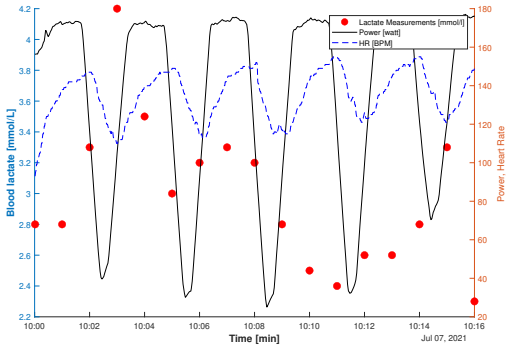
Time	2	5	8	11	14	17	20	23	26	29
RPE	6	7	8	9	9	9	9	9	10	10

Table 4.6: Subject B's RPE at Time minutes after start of day two.

Time	2	5	8	11	14	17	20	23	26	29
RPE	6	7	7	7	7	7	7	7	7	7



(a) Day two intervals subject A.



(b) Day two intervals subject B.

Figure 4.2: Day two intervals. Power, Heart Rate and blood lactate measurements are plotted.

4.1.3 Day three continuous efforts

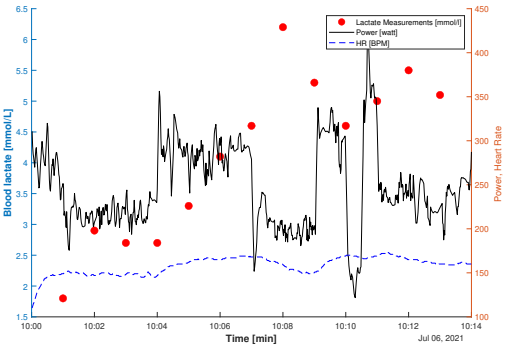
Figure 4.3 shows the results from day three of data gathering.

Table 4.7: Subject A's RPE at Time minutes after start of day three.

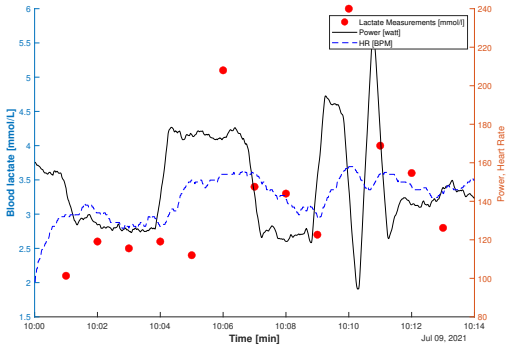
Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RPE	3	4	4	5	6	7	8	7	6	7	8	8	7	7

Table 4.8: Subject B's RPE at Time minutes after start of day three.

Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RPE	5	4	3	3	6	7	7	5	5	7	7	6	6	6



(a) Day three, subject A.



(b) Day three, subject B.

Figure 4.3: Day three intervals. Power, Heart Rate and blood lactate measurements are plotted.

4.2 Estimation results

Figure 4.4 through Figure 4.9 shows the output from the Kalman filter.

Table 4.9: Mean square error (MSE) between measurements and a priori estimated output at time of measurement. Results from three different estimation situations, first with all measurements available, second with every other measurement removed and third with now measurements available.

Subject	All measurements	Every other measurement removed	No measurements
A	0.34	0.56	0.71
B	0.87	1.55	1.01

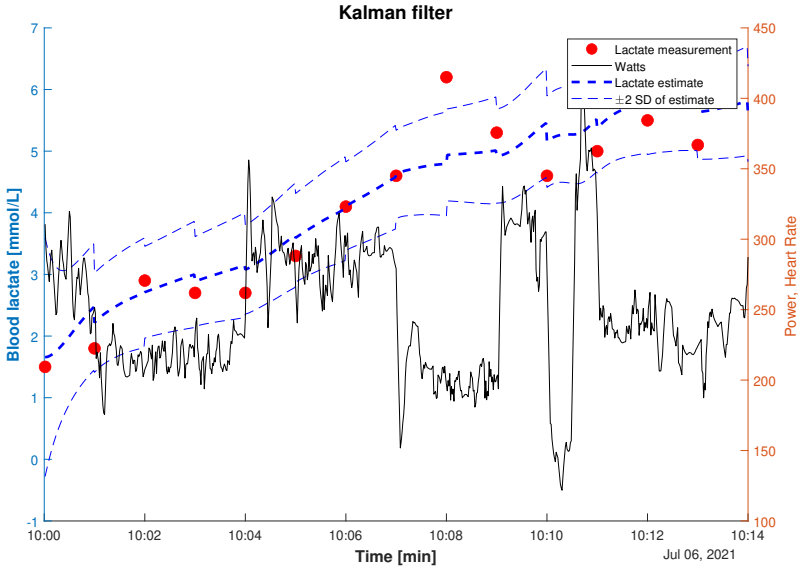


Figure 4.4: Estimation of continuous effort from subject A with all measurements available.

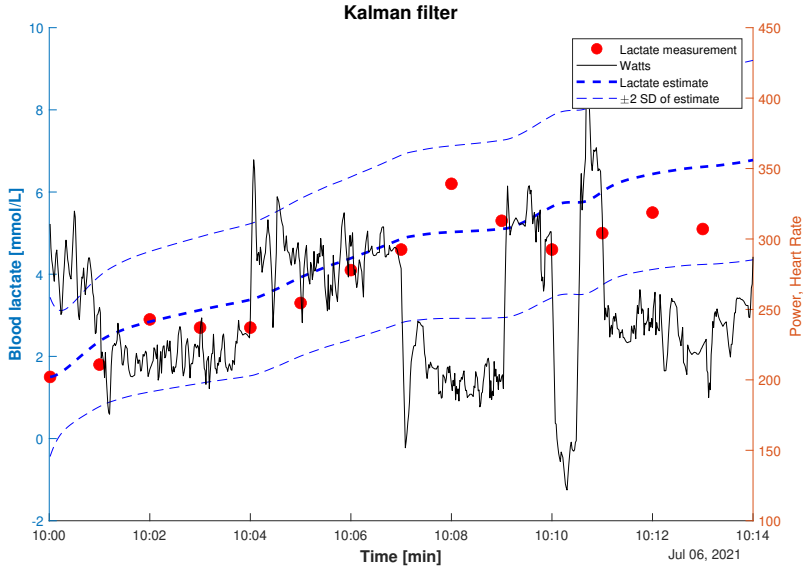


Figure 4.5: Estimation of continuous effort from subject A with no measurements.

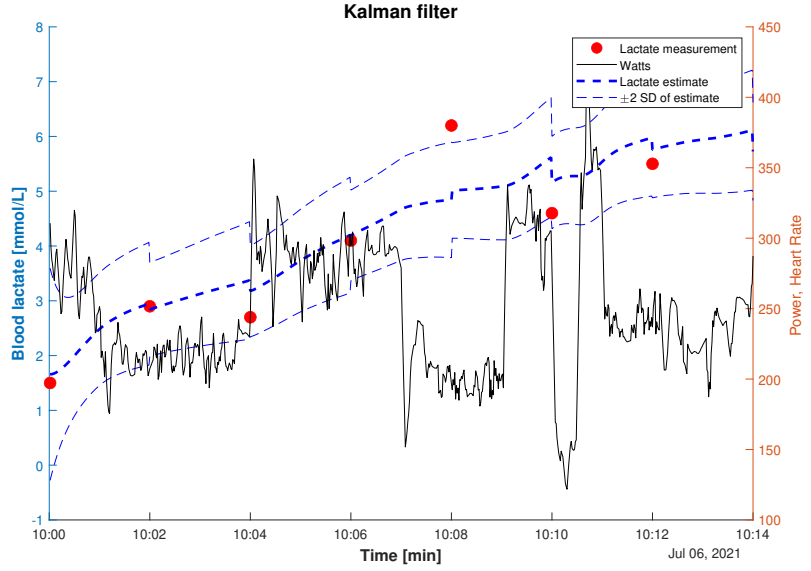


Figure 4.6: Estimation of continuous effort from subject A with every other measurement removed.

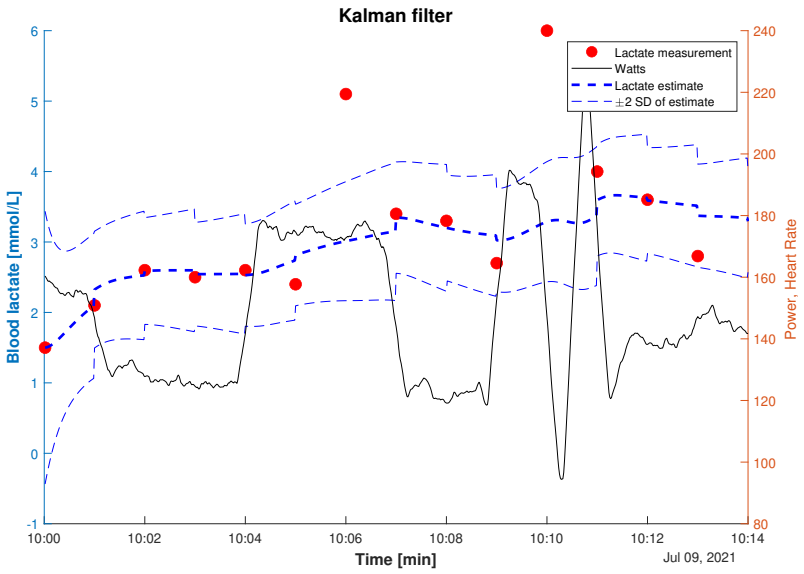


Figure 4.7: Estimation of continuous effort from subject B with all measurements available.

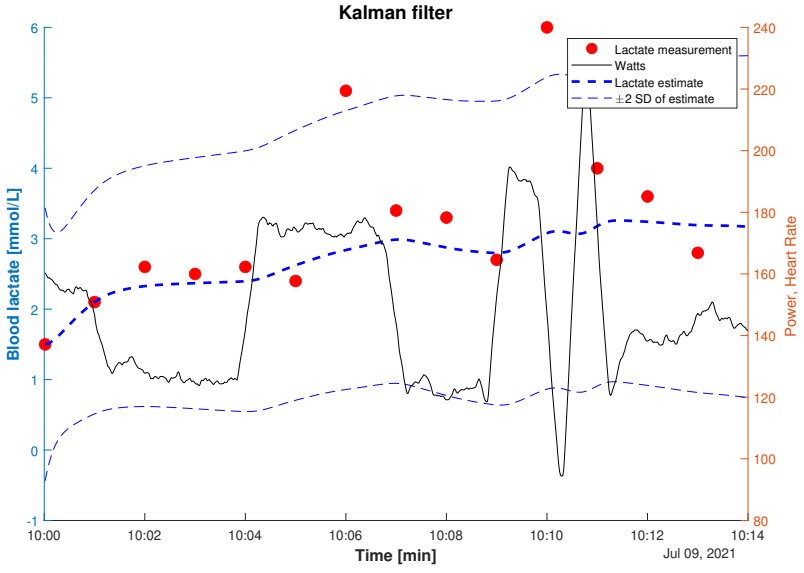


Figure 4.8: Estimation of continuous effort from subject B with no measurements.

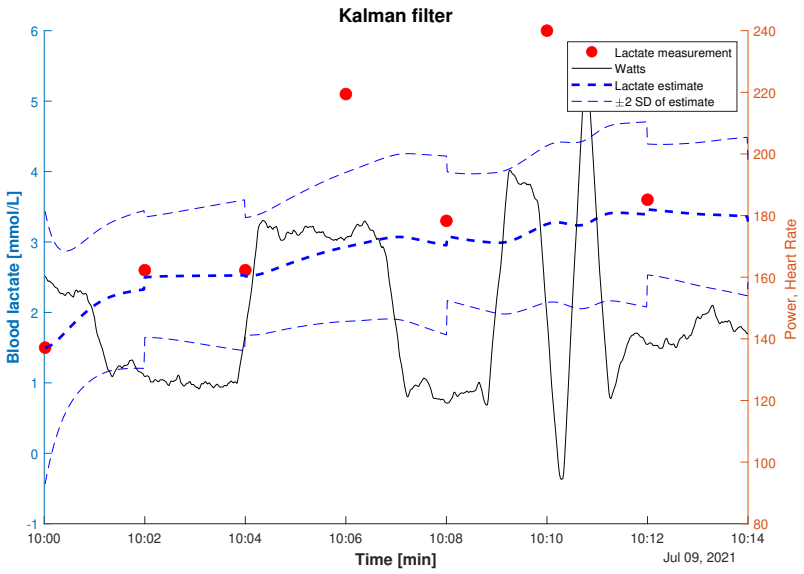


Figure 4.9: Estimation of continuous effort from subject B with every other measurement removed.

Chapter 5

Discussion

5.1 Data gathering

5.1.1 Design of test protocols

The choice of test protocols was done to try to capture different sides of each test subjects physiology. A 3x6 minute interval at 90% of the anaerobic threshold should stabilize at a lactate concentration which is sustainable. This intensity is relevant for longer endurance events that lasts for hours. A 10x2 minute interval at 110% of AT tried to elicit the cumulative fatigue of exercising at intensities above the anaerobic threshold for prolonged periods of time. Lastly the continuous bout on the third testing day was meant to simulate a race condition where the intensity is ever-changing and meant to be used as a validation data set for the estimator.

5.1.2 Reliability of lactate measurements

When following the correct procedure, with nothing going wrong the accuracy of a handheld lactate analyzer such as the Lactate pro 2 can be quite high[1]. However some samples may become contaminated and thus yielding wildly inaccurate measurements. This duality between great accuracy on one hand and great inaccuracy on the other hand creates issues when Kalman filtering. These issues are somewhat mitigated through the use of RPE and outlier detection, but nonetheless creates a problem as it may be hard to classify weather the lactate concentration is rising more rapidly than what the model predicts or if there is a bad measurement.

5.1.3 Sample size

A sample size of two is not a large sample size when developing physiological models. Each subject's lactate concentration was only measured about 50 times each over the course of three days, leaving only a little over 100 data points as the data

basis for developing a model. Naturally a large sample size with more testing days and a higher amount of test data would vastly improve confidence in any models developed. It would also ease the issues regarding reliability of the measurements as more measurements would lessen the penalty of removing bad measurements

5.1.4 Intensity control

The goal of intensity control of the intervals where for the intensity to be equal between subjects. To control the intensity the external power was used and subjects where asked to hold the power measurement at the desired power. The power was normalized between subjects by determining their anaerobic threshold and then prescribing intervals based on percentages of the subjects AT. When looking at Table 4.1 and Table 4.2 subject B's AT was set to only the second step of subjects B AT test. This is less than the three steps that is recommended by Olympiatoppen [6]. The 20 watt steps also reduces the precision when the end AT is lower than subject A's. Thus the intensity, at least the reported RPE, was higher for subject A.

5.2 Estimation

5.2.1 Accuracy

In Table 4.9 the mean square error (MSE) for subject A is lower than for subject B for all three situations with different availability of measurements. However when manually assessing Figure 4.4 and Figure 4.7 it is not as clear cut which subject has better estimation performance. The two outliers in the data set from subject B's third day likely causes the MSE to increase, but these two measurements are most likely to be erroneous due to some external contamination.

5.3 Conclusions

It hard to conclude with any amount of certainty weather or not the estimator is able to achieve what it set out to do. Both because of a lacking data foundation, but also due to the nature of uncertainty in handheld lactate analyzers that runs an inherent risk of contamination.

5.4 Further work

For further work a larger and more comprehensive data gathering process should take place. For development of broadly applicable and reliable models a larger groundwork of data is required. A data set which includes some sets that have

such accuracy and reliability that they can be considered ground truth would make development and validation of estimators easier. Other methods might also yield better results than Kalman filter approach. Incorporating heart rate and RPE more tightly into the estimation process is also something that did not make it into this report, and should definitely be investigated further.

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