Wearable Sensors, Artificial Neural Networks, and Feedback Control in Sports and Health Technology

by

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Abstract

Many athletes do not have access to a coach to help them improve their performance, and coaches' feedback can be subjective. Artificial sport coaches can collect continuous data during training and competition, analyze these data, and — by comparing the current performance with a target performance — give automatic feedback. Artificial sport coaches can make sports more accessible for athletes without coaches, and help coaches make more objective decisions. Developing artificial sport coaches can be challenging, as they require knowledge of continuous data collection outside of the laboratory, smart data analysis, and control systems. The goal of this thesis was to develop and test tools that can simplify the process of gathering objective data during sports, analyzing these data, and providing automatic real-time feedback to the athlete and the coach. First, my colleagues and I designed a generalizable approach to build a closed-loop feedback control system in sports, and tested this approach in controlling cycling power. Second, we demonstrated how a data-driven approach can simplify the process of developing complex models, by comparing the advantages and disadvantages of physics-based and neural network-based modeling for predicting cycling power. Third, we tested whether we could use a state-of-the-art image recognition to classify individual runners and their running performance. And lastly, we demonstrated how we can teach important, complex laboratory skills needed for human data collection and analysis, without the need of a physical laboratory or its expensive laboratory equipment, by utilizing the strengths of wearable sensors for remote teaching. Overall, my thesis provides emerging and established scientists and sports and health technology engineers with a better understanding of how to more easily and efficiently develop wearable measurement technologies, data analysis systems and complex models, and control systems. Additionally, it will also provide novel sports specific insights, specifically for cycling and running.

Keywords: Sports and Health Technology; Wearable Sensors; Artificial Neural Networks; Feedback Control; Artificial Sport Coach

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Chapter 1

Introduction

Wearable technology has started a new era of quantifying and improving our lifestyles. Wearable technology (also called wearables or wearable devices) refers to small, wireless devices that monitor various health related information such as vital signs (e.g., heart rate), activity levels (e.g., step counts or activity recognition), environmental variables (e.g., noise), or physical and mental fatigue [168, 197, 209, 123], anytime and anywhere. This information can indirectly improve human lifestyles by, for example incentivizing a more active and healthier lifestyle [222]. Additionally, wearables can also directly improve the quality and safety of their lives. For example, hearing aids can help hearing impaired people to hear better [186], or smartwatches can detect a medical emergency and call for help [231].

In elite and recreational sports, athletes and coaches increasingly use wearable technology to improve performance with objective, data-driven decisions. In elite sports, athletes and their teams use technology to gain a performance advantage over their opponents. Historically, coaches would visually observe athletes and provide feedback based on their subjective performance analysis. Visual performance observations in sports are limiting in the amount and accuracy of information, which also limit the quality of the following feedback [76, 115, 150, 75]. To improve performance, many coaches now provide their feedback based on objective data from measurement systems, such as motion capture systems or heart rate monitors [209, 79, 213, 155, 39]. Wearable technology can also support athletes who cannot afford or do not want to work with a coach. Technology can provide athletes without a coach with valuable, objective, and often simplified information, such as the exercise intensity calculated from heart rates [14]. The growing availability of different wearable measurement systems like smartwatches also increases the amount of information an athlete and their coach can gather at a given time. As a result, it becomes increasingly harder to analyze and interpret all this data in a meaningful way [20, 221, 235].

Artificial sport coaches can offer support for athletes and coaches. Here I define an artificial sport coach as a system that automatically measures data, analyzes the data, and provides feedback to the athlete and the coach. Artificial sport coaches can alleviate some of the coach's responsibilities, such as setting up and adjusting training plans based on real-time progress, and assist athletes without a coach in all stages of training. First, multiple measurement technologies obtain various objective data automatically, mitigating the coach's responsibility to make subjective observations. Second, a data analysis system analyzes and interprets the complex dataset, mitigating the responsibility for a coach to manually find the performance information in the data. Lastly, a control system compares the current performance with a target performance and suggests relevant improvement opportunities in real-time, mitigating the coach's responsibility to give feedback [70]. These three pieces of artificial sport coaches — measurement technologies, data analysis systems, and control systems — have been rapidly evolving in recent years.

Developing artificial sport coaches can be challenging. Even though all the individual pieces for artificial sport coaches (measurement technologies, data analysis systems, and control systems) exist, the complexity of developing algorithms for these systems can be limiting for coaches and their sport scientists without specific expertise. Because artificial sport coaches do not exist in most sports, sport scientists need to develop new algorithms, or adopt existing algorithms, assuming that they are publicly available. Developing algorithms automatic data analysis requires specifically trained experts. Adopting existing algorithms is possible, but it is yet unclear which existing algorithms would generalize well to different sports [51, 144]. Similarly, developing control systems for real-time feedback requires specifically trained experts. Each control system requires optimization for its specific application, which means that adapting control systems from one sport to another sport is very challenging [15]. For example, controlling running speed with step frequency in real-time requires an understanding of the dynamic relationship between step frequency (input) and running speed (output) [214]. Therefore, a controller that controls running speed with step frequency, won't be applicable for a different problem such as controlling cycling power with the cadence of the cyclist.

My central goal of this thesis is to develop and test tools that can simplify the process of gathering objective data during sports, analyzing these data, and providing automatic real-time feedback to the athlete and the coach (Figure 1.1). First, I will design a generalizable approach to build a closed-loop feedback control system, and test this approach in a proof-of-concept-experiment in controlling cycling power. Second, I will demonstrate how a data-driven approach can simplify the process of developing complex models — which are also required for developing the generalizable closed-loop feedback control system —, by comparing the advantages and disadvantages of physics-based and neural network-based modeling for predicting cycling power. Third, I will test whether we could use a state-of-the-art image recognition to classify individual runners and their running performance. And lastly, I will demonstrate how we can teach important, complex laboratory skills needed for human data collection and analysis, without the need of a physical laboratory or its expensive laboratory equipment. Overall, my thesis provides emerging and established scientists and sports and health technology engineers with a better understanding of how to more easily and efficiently develop wearable measurement technology, data analysis systems and complex models, and control systems. Additionally, it will also provide novel sports specific insights, specifically for cycling and running. My goal will not be to develop a fully functioning artificial sport coach, but to develop and test different tools for sports and health technology engineers to do so.

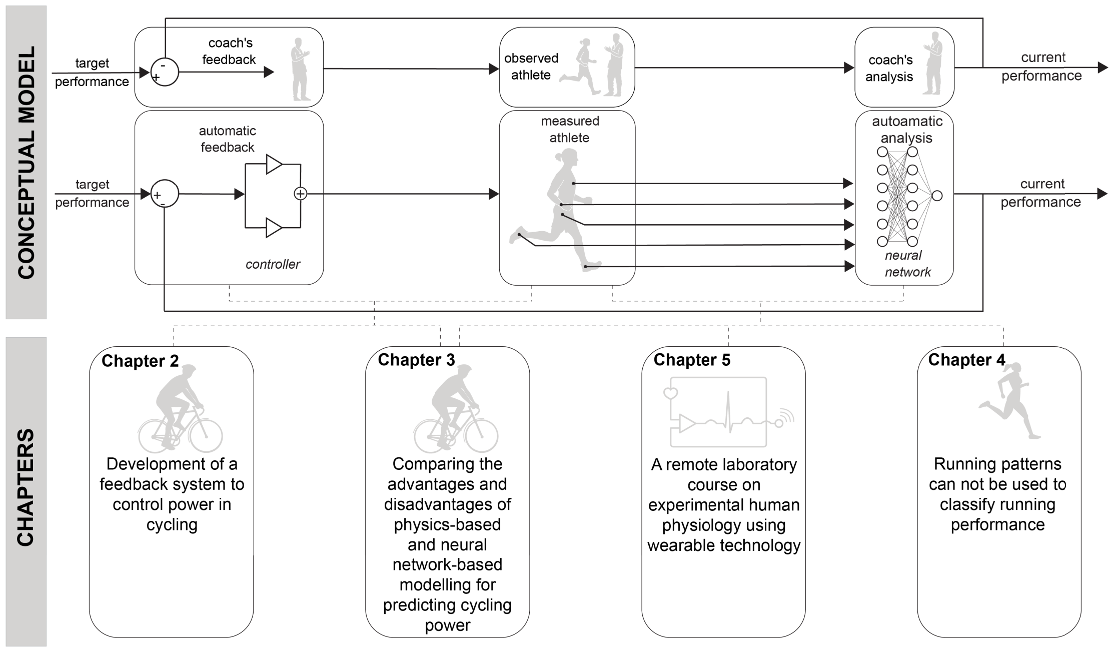

Figure 1.1: The conceptual model of how an automatic feedback system can support a coach's feedback loop, and how each aim relates to the different pieces of the feedback loop.

1.1 Improving Sports Performance of Athletes with Technology

To become better in any sport, an athlete needs to implement a continuous loop of planning, realization, control, and evaluation [70]. Figure 1.2 illustrates these four performance optimization phases. Planning ensures that the athlete reaches peak performance just in time for their competition through exercises and recovery, and involves many factors such as the competition calendar, cyclization of sports training sessions, or the types of training. Realization involves everything that happens during the training, such as preparing equipment, evaluating the physical and psychological condition of the athlete before the training session, instructing exercises, monitoring the intensity of the training session, and improving tactics in teams sports disciplines. Control is the gathering of information during training, and the comparison between planned and performed exercises. Evaluation compares the athlete's current performance with the target performance, which sets the foundation for further planning.

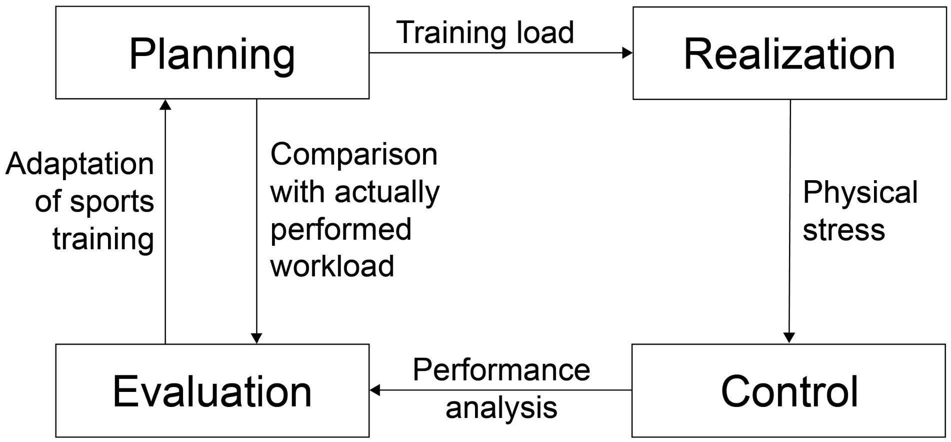

Figure 1.2: The continuous loop of planning, realization, control, and evaluation [70]

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Coaches can support athletes during all four training phases, or athletes can train themselves. Coaches plan the training sessions. During training, competition, and recovery they instruct, observe, gather information, and adjust accordingly. Coaches then evaluate the current performance based on the gathered information and adapt the training plan [124]. An athlete might have one, or multiple coaches for different parts of the training. Alternatively, they might have no coach at all, for example for financial reasons, and therefore coach themselves. When I mention a coach in this thesis, it can be either multiple coaches, one coach, or no coach at all.

Coaches can be subjective. Traditional feedback relies on the coach's subjective observations and previous experiences. However, these subjective observations can be both inaccurate and unreliable. Different studies in football have shown that a coach's ability to recollect key factors that determine performance are somewhere between 40% and 60%, depending on the skill level of the coach and whether they take notes [76, 115, 150, 75]. These results are not surprising, considering how complex the processes of committing and retrieving memory to and from our brain is. Our brains can more easily remember critical situations when compared to non-critical situations [87]. In combination with the coach's emotions and biases, this can lead to a distorted perception of performance and biased feedback [75].

To measure performance more objectively, coaches can use technology. Many measurement devices can quantify or estimate important components of physical fitness such as cardiorespiratory endurance (e.g., metabolic cart), muscular strength and endurance (e.g., isokinetic dynamometer), or muscular power (e.g., force plate). Many new technologies now also allow the quantification of an athlete's sport specific technique, by analyzing their movement patterns using motion analysis with video or wearable sensors [78, 62, 24, 165, 162]. Wearable sensors such as smart watches can measure day-to-day physiological parameters that can give an indication of their general health, fitness, and recovery [109]. For team sports, cameras and wearable sensors give the coach a clear picture of the team's movements [236].

Due to vast and complex datasets from athletes, coaches need to make use of data analysis systems to extract meaningful information. Vast, complex datasets are commonly called big datasets, and there are 5 main properties defining them: Volume, Velocity, Variety, Veracity, and Value. Volume defines the vast amount of data. Velocity is the speed at which data accumulates. Variety describes the different data formats that result from many different measurement technologies, such as video, or data from wearable sensors. Veracity relates to the quality of the collected data. Lastly, there might be value in the data, but if it is never discovered, it is of no use [20, 177]. Having a dataset that consists of these 5 properties can make it challenging for a coach to extract important information and make future decisions without additional help from technology. Therefore, data analysis systems, such as mathematical models, computational intelligence, data mining, and deep learning, can help organize these data, and find patterns that are otherwise hard to identify [70, 39, 20, 194, 219].

Control systems can then support the athlete and the coach by providing automatic and objective feedback. Control systems can receive performance information, and based on the difference between the current performance and the target performance, give recommendations on how to improve in real-time [15, 101]. In sports they can help control the realization of training and recovery, as well as evaluate and plan future steps for both athletes with and without a coach. Control systems can monitor each individual athlete by observing objective data and giving real-time feedback. Kuwahara et al. developed a system that can give visual and auditory feedback based on center of pressure and posture estimation measurements to teach novice snowboarders to better transfer their weight [114]. A smart coaching assistant at the Universidad Católica San Antonio de Murcia volleyball team measures both effort and exercise quality and gives real-time feedback to the coach and the athlete [239]. Control systems can also control athletes movements in real-time, where coaches can't. For example, software can help to control an athlete's running speed, by adjusting their step frequency in real-time [214], or heart rate information can guide the speed of an athlete in real-time [35]. To test how control systems can evaluate the current performance and create future training plans, Mata et al. [129] created an application that recommends training and meal plans to athletes, based on fitness tests, with the help of semantic cross-information from social networks, and validated their plans with specialists.

1.2 Measurement Technologies

Humans use biomedical and biomechanical measurements to quantify their health and performance. Biomedical measurements detect biophysical, biochemical, or bioelectrical changes in the body [173]. For example, they can measure vital signs such as heart rate, electrocardiogram (ECG), blood pressure, and respiratory rate. Measuring our vital signs can also indicate our performance. For example, heart rate, lactate threshold, and maximal oxygen uptake (VO_{2max}) provide insights into aerobic fitness [13, 37, 199]. Biomechanical measurements analyze movement and forces within the body, providing insights into physical fitness, musculoskeletal health, and overall functional capacity [90]. For example, clinicians can use gait analysis to detect neuromuscular conditions or train older individuals to prevent falls [248, 249, 32], and coaches can use it for running performance assessment [117, 147, 100, 92].

In sport biomechanics, kinematics and kinetics are specifically important to study movements. Kinematics characterizes motion independently of the forces involved, focusing on measurements of joint angles and segment displacements. Kinetics investigates the forces, torques, and muscle activations responsible for creating or modifying observed motion. These two disciplines work together to provide a comprehensive understanding of human motion and its underlying mechanical principles [172, 255, 228, 119, 252]. For example, in running gait analysis researchers can measure the movements of the body segments through motion analysis with video and other technologies, ground reaction forces and other plantar forces produced through force plates and plantar pressure insoles, or muscle activation distribution with electromyography (EMG) [172, 233, 166].

Most of the gold standard biomechanical technologies for sports performance are constrained to relatively unrealistic laboratory settings. Typically, scientists obtain various measurements of athletes in their laboratories, where they have measurement systems such as video cameras, force plates, instrumented treadmills, and EMG systems [252, 254, 225, 180, 244]. Although these systems are the gold standard in estimating various performance metrics, laboratory-based experiments have several disadvantages. First, the equipment is often expensive. Second, laboratory-based measurements can be unrepresentative of real-life situations. In running gait analysis, for example, indoor overground running or treadmill running can be unrepresentative of running in outdoor environments [58, 33, 17]. Lastly, laboratory-based experimentation is restricted for some sports such as ski jumping that cannot be measured inside of laboratory facilities.

1.2.1 Wearable Measurement Technologies

In recent years, wearable sensors have emerged as a modern technology that enable continuous health and performance monitoring outside of the laboratory. Wearable sensors are microelectromechanical sensors that can respond to many physical variables and measure biophysical, biochemical, or bioelectrical signals. The combination of low power computing and the internet of things (IoT) enables the development of wearable sensors with long battery life which can be integrated into accessories, or placed into the human body, to measure biomedical and biomechanical variables over long periods of time and outside of the laboratory [197, 209, 228, 252, 238, 5, 29]. For example, smart watches combine many sensors and measure variables such as heart rate and variability, skin temperature, or motion [109]. To analyze kinematics specifically, inertial measurement units (IMUs) can measure the positions and movements of body segments and joints [122, 184]. For kinetics, pressure insoles, cameras, or single IMUs estimate ground reaction forces [74, 73, 108, 36, 230, 118, 105], and wearable EMG systems can measure muscle activities [3, 9, 4].

Even though wearable sensors have potential for outside-of-the-laboratory measurements, they can also have measurement performance issues. Measurement issues with wearable sensors include drift, external interference, or nonlinear properties. Drift is the gradual accumulation of errors that cause a deviation between the estimated and the true state of a sensor, which can for example lead to measurement inaccuracies when estimating body positions or joint angles with IMUs. External interference happens when electromagnetic fields or signal cross-talk between sensors disrupt or corrupt a sensor's measurements. Nonlinear properties can be a problem when scientists try to indirectly measure or estimate a physical variable. For example, when scientists try to estimate ground reaction forces with FSR (Force-sensing resistors) sensors in the shoe, the nonlinear properties of the FSR sensors can make it challenging to accurately estimate ground reaction forces [252].

With special algorithms, scientists are able to improve measurement performance of wearable sensors. Simple filters, such as high-pass or low-pass filters, can remove unwanted noise in the measured data [64]. More complex filters, such as Kalman filters, combine measurements with predictions and can help to more accurately estimate the sensor's state, and reduce drift, noise, and external interference [122, 64, 247, 261]. Sensor fusion, which is the combination of multiple sensors, can achieve similar results or even indirectly estimate variables from the combination of different measurements [64, 85, 202]. Lastly, machine learning algorithms, such as artificial neural networks, can assist in most of these areas as well, enhancing wearable sensor measurements by, for example, reducing drift or incorporating sensor fusion [89, 189, 113, 152].

Nowadays, many wearable devices can accurately measure many biomechanical variables. Different reviews have looked into the measurement performance of wearable sensors in different movement analysis situations. These reviews include the measurements and quantifications of jump counts and external loads [245], barbell velocities [44], jump height [43], lower extremity kinematics during running [256], joining angle estimation [185], or general tracking of human motion [78]. Most reviews found that reliability and validity is generally good to excellent, but the results depend on the movements, as well as the measurement systems. For example, the full-body IMU suite from xSens (Movella Inc., Henderson, USA) can accurately measure lower body kinematics in the sagittal plane, but lacks accuracy in the frontal and transverse plane [165]. Similarly, the myoMotion system (Noraxon USA, Scottsdale, USA) can accurately measure stance phase, but needs more evaluation for the swing phase during gait analysis [175]. EMG systems can now be fully wearable [60], and pressure insoles are becoming more accurate in estimating ground reaction forces [108, 171].

1.3 Data Analysis Systems

To understand and predict natural phenomena such as performance and health in an athlete, data analysis systems can utilize mathematical models. Models describe how a plant transforms one or multiple inputs into one or multiple outputs, where the plant is the object the real-world phenomenon is acting on (Figure 1.3). For example in modeling cycling, the cyclist and the bike would be the plant, variables such as the speed and different resistances could be the inputs, and the power would be the output. By being able to accurately predict output variables based on the input variables, scientists can then gain a better understanding of specific phenomena, and subsequently create tools that improve a certain situation based on this understanding. For example in cycling, mathematical models can help better understand how better cycling position can reduce power [56, 203, 63]. They can also help us simulate and optimize pacing efficiency based on variables such as the race length, the hill profile, and the cyclist's cardiovascular endurance [40, 227, 16, 253].

Figure 1.3: Illustrates the mechanism of a mathematical model, where an input influences a plant and subsequently its output.

In general, we can distinguish between physics-based models, data-driven models, and models that are a hybrid of those two. Here, we define models that aim to understand and apply natural principles and assumptions underlying a particular natural phenomenon as physics-based models. Where physics-based models rely on these natural principles to identify an input-output relationship of the plant, data-driven models rely on the data itself [215]. Data-driven models use statistical and machine learning techniques to learn patterns and relationships in the data, and therefore heavily rely on the quality and quantity of the data used to build the model [215]. Hybrid models combine physics-based and data-driven models [192]. These models incorporate assumptions and constraints from natural principles into statistical and machine learning models. In the remainder of this thesis, I will focus on physics-based and data-driven models.

1.3.1 Physics-based Models

Scientists develop and validate simple to complex physics-based models to gain a better understanding of natural phenomena. Using their understanding of the fundamental laws of nature, scientists create mathematical models that incorporate variables representing measurable quantities in the real world. Simple models can provide scientists with a fast, but often less accurate, understanding of natural phenomena. Simple models use a minimum amount of parameters to describe natural phenomena, which makes them easier to develop and faster in computations. In contrast, they can lack accuracy and restrict applicability, as they often rely on specific assumptions that narrow their range of real-world scenarios and conditions [11]. Consider this model that my colleagues and I recently developed which predicts mechanical power during street cycling [136]:

$$P_p = mv\dot{v} + cv^3 \tag{1.1}$$

where P_p is the mechanical power at the pedal applied by the cyclist, m is the mass of the cyclist and the bike, v is the speed, $\dot{v}$ is the acceleration, and c is the drag. This model is relatively simple, as it only requires measurements of the speed, the mass, and either estimates or measurements of the drag. Complex models can provide scientists with a more realistic understanding of natural phenomena but are more challenging to develop and use. Complex models incorporate more parameters to describe real-world phenomena more accurately. They are more realistic, but require a better understanding of the fundamental laws of nature to develop and more computational power during application. For example, in 1998, Martin et al. developed and validated a cycling model [128] which aimed to accurately predict cycling power during steady state cycling. In their model they considered many resistances that we did not consider in equation 1.1 (Table 1.1):

$$\begin{aligned} P_{\mathrm{TOT}} = \Big[& V_a^2 V_G \frac{1}{2}\rho(C_D A + F_W) + V_G C_{RR} m_T g + V_G(91 + 8.7V_G)10^{-3} \\ & + V_G m_T g G_R + \frac{1}{2}(m_T + \frac{l}{r^2})(V_{Gf}^2 - V_{Gi}^2)/(t_i - t_f)\Big]/E_c \end{aligned} \tag{1.2}$$

Besides the advantage of better understanding natural phenomena, using a physics-based approach to develop models also introduces some challenges. First, this process can require a detailed understanding of the principles underlying a process, which may be unknown or complex. For example, to predict cycling speed from cadence, a scientist would have to understand the underlying principles of how the angular velocity of the pedal translates to the linear velocity of the wheel. Second, a physics-based model may require measurements of

Table 1.1: Parameters and their definitions for equation 1.2.

Parameter	**Parameter Definition**
V_a	Air velocity
V_G	Ground velocity
ρ	air density
C_D	Coefficient of drag
A	Frontal area
F_W	Incremental drag area of the spokes
C_{RR}	Coefficient of rolling resistance
m_T	Total mass of cyclist and bike
g	Gravity
G_R	Road gradient
I	Moment of inertia of wheels
r^2	Wheel radius
V_{Gf}	Final ground velocity
V_{Gi}	Initial ground velocity
t_i	Initial time
t_f	Final time
E_c	Chain efficiency factor

fixed parameters. This is not just more time consuming but can also introduce measurement inaccuracies, which stem from equipment measurement errors, and the fact that nothing can be measured perfectly. Inaccurately measured parameters can subsequently reduce the performance of the overall model. In predicting cycling speed from cadence, the scientist would have to measure bike parameters such as the wheel radius.

1.3.2 Data-driven Models

Data-driven models can automatically find patterns in the data, introducing some advantages over physics-based models. Data-driven models rely on data to capture and represent relationships between input and output variables [215]. Because data-driven models can learn from data without the need of understanding the underlying principles, there are many applications. Modeling the input-output relationship of processes with data-driven models still requires knowledge about the input variables. But, given enough data, they can approximate a wide variety of input-output relationships without explicitly having to measure fixed parameters, or understand the principles underlying a process, ameliorating the two challenges identified with physics-based models [98]. For example, to predict cycling speed from cadence a data-driven model could learn the relationship between the cadence and the cycling speed without understanding the principles that relate cadence to speed, and without requiring measurements of the bike parameters, such as the wheel radius.

Not many scientists have directly compared the performance of physics-based and data-driven models so far. In biomechanics, one recent study compared a neuromuscuskeletal model with a neural network model in estimating joint torques [257]. The neural network improved the prediction accuracy significantly over the neuromuscuskeletal model. In other areas of engineering, such as in predicting different metrics in motorized vehicles, scientists also found superior performance of neural networks, and concluded that using neural networks could be simpler over physics-based models, because there are often less measurements required [42, 102].

Machine learning is a branch of data-driven modeling, and encompasses three primary categories: supervised learning, unsupervised learning, and reinforcement learning [126]. Machine learning algorithms are popular due to their ability to automatically learn patterns from data to make new predictions on new data. In supervised learning, the algorithm learns to make predictions from labeled data. For example, scientists can train machine learning algorithms to identify different running surfaces from wearable accelerometers. Scientists first label the data with the surface, and train the algorithm accordingly [59]. Unsupervised learning refers to training an algorithm on unlabeled data, allowing it to discover hidden patterns or structures within the data itself. For example, when doing a cluster analysis on rearfoot runners, Senevirathna et al. [207] found two distinct running patterns. In reinforcement learning the algorithm continuously learns by making decisions and getting rewards or penalties based on the outcomes of these decisions. Reinforcement learning can for example make robots learn how to play football [52]. In this thesis, I will focus on supervised artificial neural networks.

Artificial neural networks are one of the most popular machine learning tools due to their ability to learn complex patterns from raw data sets, but need a high amount of computational power. Artificial neural networks are named as such because they loosely imitate the human brain [181]. In their simplest form, they consist of interconnected nodes organized in layers [6]. Each node receives input data, performs a weighted computation, and produces an output. During training, a process called backpropagation computes the gradients of the neural network weights by propagating the errors between the target and the actual value backward from the output layer to the input layer. It can then adjust the nodes' weights and biases to learn complex non-linear patterns in the data. For a long time, the need for vast computational power during the training process restrained artificial neural networks for proper application, but with grid and cloud computing, it has become one of the leading machine learning techniques in recent years [6, 149] I chose to use artificial neural networks in my research, because, due to their capability of nonlinear computations, they are particularly good at learning complex patterns from raw data.

Recurrent Neural Networks (RNNs) are specifically useful to learn from time series data, but in their basic form they lack in remembering long-term dependencies. RNNs consist of interconnected layers of nodes that can maintain an internal state capturing information from previous time steps [146]. This internal state gives RNNs particular strength with time series data analysis, such as natural language processing [232]. One key challenge in training RNNs is the vanishing gradient problem. The vanishing gradient problem refers to a difficulty that arises when training RNNs. During the training process, RNNs update their weights by calculating gradients, which indicate the direction and magnitude of adjustments needed for optimal performance. However, these gradients can become extremely small over time, which can make it challenging for the RNN to learn long-term dependencies in the data. Essentially, the RNN struggles to remember information from earlier time steps, hindering its ability to make accurate predictions or model complex patterns. [23, 96, 176, 80].

To address the vanishing gradient problem in RNNs, scientists have developed advanced RNN architectures, such as Long-Short-Term Memory (LSTM) layers. LSTM layers are a type of RNN layer that can selectively remember or forget information over time, allowing the network to capture long-term dependencies more effectively [6, 84, 242]. This memory component of a node is defined as the cell. LSTM nodes consist of three main components: an input gate, a forget gate, and an output gate. The input gate controls how much new information the node adds to its cell state, while the forget gate controls how much old information it retains. The output gate determines how much of the cell state the node uses to compute the output at each time step. By gating the flow of information in this way, LSTM layers can selectively remember or forget information over long time scales, allowing them to capture complex long-term dependencies in sequential data.

For time-invariant grid-like data, such as images, Convolutional Neural Networks (CNNs) are common solutions. Convolutional layers apply a filter, also called kernel, which is a small matrix of weights to the input data [170, 88]. This process performs element-wise multiplication of the filter values with the original values of the input in a localized region. The filter slides across the whole input, enabling the model to detect local patterns regardless of their position in the input. CNNs demonstrate success in various computer vision tasks, such as image recognition [174]. Though the vanishing gradient problem is not as common with CNNs as it is with RNNs, it can become an issue as the depth (number of layers) of the network increases [93].

To address the vanishing gradient problem in deep CNNs, scientists have developed advanced CNN architectures, such as Residual Networks (ResNet). ResNet introduces the concept of residual connections, also called skip connections, which allow the network to bypass certain layers, effectively creating shortcuts for the flow of information [93]. These connections help mitigate the vanishing gradient problem, enabling the training of much deeper networks without suffering from performance degradation. With residual connections, ResNet can leverage the power of deep architectures, capture complex hierarchical features, and improve generalization capabilities.

1.4 Control Systems

Control systems can improve our lives, but are complex to develop and analyze. In a control system, a controller controls a plant, which has one or more input variables and one or more output variables. The purpose of the control system is to minimize the error between a target variable (setpoint) and the output variable (actual value), by changing the input to the plant, also called the control signal (Figure 1.4). For example, in cruise control, the car is the plant, and the control system aims to minimize the error between the target speed and the actual speed by adjusting the voltage supplied to the electric motor. Control systems have applications in many parts of life. Thermostats control the temperature in buildings, washing machines have systems that control water levels or temperature, and aircrafts have systems that continuously adjust the aircraft's position, altitude, and orientation. In control systems, there are two or more dynamical systems — which are systems that exhibit changing behavior over time, often in response to external stimulation — interacting with each other: at least one controller and at least one plant. Analyzing control systems can be challenging because the mutual influence between thee interconnected dynamic systems makes it difficult to determine a clear cause-and-effect relationship [15]. Developing stable control systems can therefore be a very complex task.

Generally, there are two types of feedback control: open-loop and closed-loop control. In an open-loop system (Figure 1.4 a), the input of the plant is independent from the output. Consider the delivery of insulin for the management of type 1 diabetes. Traditionally, patients used an open-loop process, which involved manual injections of insulin at regular intervals throughout the day based on estimated insulin requirements. Open-loop systems are relatively simple, cost-effective and fast, but they are less stable in complex environments. In type 1 diabetes management, open-loop delivery relies on the patient's and their doctor's ability to accurately estimate their insulin requirements. This means that open-loop control requires an accurate model of the plant. In a closed-loop system, the input is dependent on the output (Figure 1.4 b). A closed-loop system in insulin delivery continuously monitors blood glucose levels and automatically adjusts insulin delivery through an insulin pump [91]. Closed-loop systems, though more costly and more complex to develop, are more stable in complex environments where there is no accurate model of the plant, due to their self-adjusting nature.

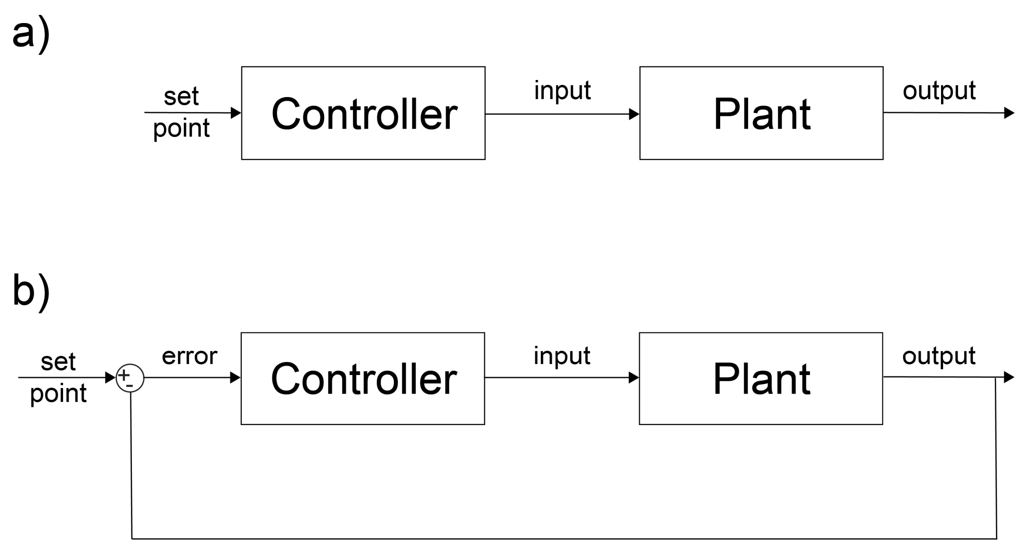

Figure 1.4: a) illustrates open-loop control, where a controller changes the input for the plant without calculating the error between the plant's output and the set point. b) illustrates closed-loop control, where the controller changes the input for the plant based on the error between the plant's output and the setpoint.

Open-loop dynamics can serve as a foundation for developing closed-loop control systems. By studying and understanding the open-loop dynamics of a system, scientists can construct mathematical models to describe the system's behavior. With these mathematical models, scientists can analyze the open-loop response to different inputs, to get a better understanding of its natural frequencies, time constants, and stability in different environments. This understanding can then lead to the development of stable closed-loop controllers that optimize its control on the plant. For example, in closed-loop insulin delivery for type 1 diabetes patients' open-loop analysis enables the individualization of the closed-loop settings for type 1 diabetes patients [54].

Most scientists and engineers use proportional-integral-derivative (PID) control, because it is both simple and stable. PID control aims to regulate the system's output by continuously adjusting the plant's input based on the error between the output and the setpoint. The proportional error measures the absolute difference between the setpoint and the output of the system. The integral error measures the accumulated sum of past errors over time to consider steady-state errors and biases. The derivative error measures the rate at which the error is changing over time to predict the future behavior of the system and dampen the response. Each error gets multiplied by a pre-set gain, to either increase or decrease its effect on the controller behavior. The controller adds up the three resulting values to determine the current control signal of the controller to the plant. PID controllers often only use one or two of its gains. For example, the derivative error can be very sensitive to noise in the system, which is why many controllers only use the proportional and integral gains [15].

1.4.1 Existing Feedback Control Systems in Sports and Health

Many applications of biofeedback systems exist in general health already. These applications can help children, grown-ups, as well as elderly people maintain or improve their physical and mental health. For example, controlling the heart rate variability through breathing exercises with visual feedback reduces physical pain and stress, and decreases the mortality and morbidity of diseases [61, 120, 81, 19, 187]. Biofeedback systems can also help patients with balance and gait disorders, by measuring their postural sway with wearable sensors, and providing visual, auditory, or tactile feedback on time to prevent a loss of balance [125].

In sports, only a few applications exist so far that aim to help athletes prevent injuries or improve their performance with biofeedback. When including all systems that used any method of intelligent data analysis methods or feedback in sports, Rajsp and Fister [194] found only 72 peer-reviewed and published projects in total between 2015 and 2019, and only the smallest amount of these projects included both the analysis as well as the real-time feedback to the athlete and the coach. Many feedback systems exist in running [241]. To reduce the risk of running-related injuries, for example, Van den Berghe et al. [240] developed a music-based feedback system that trains runners to reduce tibial shock. Other systems can help athletes to better pace themselves with music [214], or suggest training and meal plans based on real-time information about the athlete [129]. Some examples also exist in other sports. For example, Kuwahara et al. [114] developed a system that could help novice snowboarders improve their technique with both auditory and visual feedback.

In volleyball, Vales-Alonso et al. [239] developed a system that estimates athletes' energy expenditure and movement quality to adjust the training for each individual in real-time.

1.5 Laboratory vs. Wearable Sensors in Education

Educators typically hold biomedical and biomechanical laboratory courses in physical laboratories which can limit students in their education. To learn how to develop and use biomedical and biomechanical measurement and analysis systems to quantify athletes, students typically need to be in a physical laboratory. In conventional laboratory courses, a small number of relatively expensive and specialized laboratory equipment, such as instrumented treadmills or video analysis systems, often enable students to get hands-on experience in a face-to-face setting. But, being tied to laboratory equipment can limit students in their education as well as their work with athletes. First, offering hands-on experience only in person can restrain students from participating. Some students might have constraints to attend classes, for example because of physical or other health limitations, or because of remote living arrangements. Similarly, epidemiological or environmental situations (i.e., pandemics, floods, wildfires) might constrain some, many, or all students and faculty from attending in-person classes. Second, learning how to use gold standard laboratory equipment is important, but being constrained to only laboratory equipment restrains students from quantifying athletes' health and performance in real-life situations.

Remote classes could create an effective and inclusive learning environment, but delivering laboratory experiences in biomedicine and biomechanics remotely is challenging. There is a substantial body of evidence about the effectiveness of online teaching in general. Some studies even suggest that learning outcomes for online courses can be as good if not better than traditional learning, and can even lead to a stronger sense of community among students and a reduction in course withdrawal [163]. But, for laboratory experiences specifically, a commonly held view is that online teaching methods are not equivalent alternatives to conventional laboratory experiences [169, 106, 243]. Consequently, there are not a lot of options for remote laboratory courses. Universities and their students felt that lack particularly during the COVID-19 pandemic when safety necessitated the cancellation of all face-to-face classes for over a year.

Wearable technology can enable effective, inclusive, and remote laboratory experiences, and prepare students for objective and realistic measurements of athletes. First wearable technology can be budget friendly. A set of microcontroller-based sensors that can for example measure EMG and ECG, or classify activities can be as cheap as a textbook [137]. Second, wearable sensors are small, which means that universities can ship them to their students. Third, there is agreement in the athletic and scientific community that wearable sensors are revolutionizing sports and health technologies [259, 208, 250, 223]. Students should learn how to build and use these technologies so that they can gather objective information from athletes in realistic scenarios.

1.6 Chapters Overview

Chapter 2: I developed a generalizable approach to build a closed-loop feedback control system, and tested this approach in controlling a cyclist's power output. I first built a microcontroller based measurement system that measured mechanical power via the torque and the cadence of an SRM powermeter, and commanded cadence transmitted via a metronome in earphones. To understand a cyclist's dynamic behavior, I had one proof-of-concept participant match their cadence to a range of commanded cadences. I then developed a mathematical model that predicts the power as a function of commanded cadence and gear ratio. I used this model in a feedback control simulation, where the model simulated the real cyclist, and optimized for the controller modifications. I then implemented these modifications into the microcontroller-based cycling system. In real-time, the microcontroller changed the commanded cadence based on the error between a target power and the measured power. Chapter 2 provides sports scientists with a simple and generalizable approach of building a feedback control system through simulations, and demonstrates how we can control an athlete's actions accurately during training. This chapter is equivalent to our peer-reviewed conference paper [143].

Chapter 3: To test whether we could simplify developing a model with a data-driven approach, I compared a physics-based model with a neural network model in predicting cycling power. With the microcontroller-based system developed in Chapter 2, I tested 12 participants as they followed changes in cycling cadence transmitted through a metronome beat in the earphones and measured their cadence and power. I developed and trained a physics-based model and a simple neural network model, where both models had cadence, derivative of cadence, and gear ratio as input, and power as output. Chapter 3 demonstrates how scientists can leverage data-driven methods to simplify the process of developing models. This chapter is equivalent to our published bioRxiv paper and is currently awaiting peer review from a scientific journal [136].

Chapter 4: I tested whether we could use a state-of-the-art image recognition algorithm to classify individual runners and their running performance. I used data previously collected by the SFU Run Lab where participants ran on treadmill and overground with insole-implemented IMU sensors that measured linear accelerations and angular velocities [160]. I trained an existing image recognition algorithm with spectrograms of the data, to classify individual runners as well as their personal running performance based on 10 km personal best times. A secondary purpose of this project was to determine how the model's accuracy changes with changing numbers of runners and amount of training data per runner. Chapter 4 demonstrates how scientists can leverage state-of-the-art image recognition algorithms in biomechanical movement analysis and gives new insights into the individuality of running patterns, and whether or not there are good and bad running patterns.

Chapter 5: I demonstrated how we can teach important, complex laboratory skills needed for human data collection and analysis, without the need of a physical laboratory or its expensive laboratory equipment. First, I defined principles that should allow students to conduct insightful experiments. I then prototyped and developed all laboratory resources including the microcontroller-based hardware, the software to collect and analyze data, and the written and video recorded lab manuals. I taught the course with Dr. Jim Carter, who developed the lecture materials, and analyzed students' feedback. This project provides educators with a proven concept, as well as open-source resources, to teach students how to build measurement systems, and collect and analyze human data, remotely. This chapter is equivalent to our peer-reviewed journal paper [137].

Chapter 2

Development of a feedback system to control power in cycling

2.1 Abstract

Here we seek to control mechanical power output in outdoor cycling by adjusting commanded cadence of a cyclist. To understand cyclist's dynamic behaviour, we had one participant match their cadence to a range of commanded cadences. We then developed a mathematical model that predicts the actual mechanical power as a function of commanded cadence. The average absolute error between the predicted power of our model and the actual power was 15.9 ± 11.7%. We used this model to simulate our closed-loop controller and optimize for proportional and integral controller gains. With these gains in outdoor cycling experiments, the average absolute error between the target and the actual power was 3.2 ± 1.2%, the average variability in power was 2.9 ± 1.3%, and the average responsiveness, calculated as the time that the actual power requires to reach 95% of the target power following changes in target power, was 7.4 ± 2.0s.

2.2 Introduction

Wearable sensors quantify our everyday lives by counting our steps, calories, heartbeats, and more [157]. This provides us with valuable feedback about our lifestyle and can encourage us to increase our exercise intensity and improve our health [158]. While such encouragement is useful, it is still up to the person to determine how to achieve this improvement. Instead, control algorithms that can use such wearable sensor feedback to regulate user's behavior could be more effective support people in reaching their athletic and physiological goals.

Endurance sports is an area where we can implement such control algorithms and help athletes to better pace themselves. Currently, endurance athletes are intrinsically poor at pacing. For example, self-paced runners have pacing errors of 4-8% with a coefficient of variation around 3% [86, 214]. On a 10 km race, this would add up to a substantial error of

2-4 minutes given a target time of 50 minutes. Similarly, in 4 km cycling time trials, cyclists had pacing errors of 2.5% with a coefficient of variation of around 3.5% [15].

Technology can help athletes to better pace themselves. Our lab recently developed a system to improve pacing in running. A closed-loop feedback control system measured the user's current running speed and compared it to a target speed. Based on the difference, the controller adjusted the commanded step frequency for the runner in real-time. This system reduced the pacing error to under 1% [214].

In this paper we develop a system that controls athlete's mechanical power output in cycling. We accomplished this using a closed-loop feedback control system that adjusts the cadence of the cyclist in real-time. In a simple system, at a fixed gear ratio, an increase in cadence is directly proportional to an increase in power. However, in practice, other parameters such as acceleration and drag, make this relationship more complex. To get accurate control authority over the cyclist, our first step was to understand the dynamics of the system. To do so, we first built a microcontroller-operated system that provides the cyclist with changes in cadence and measures the power output. Using these data, we developed and parameterized a mathematical model that best fit the simulated power to the actual power. We then used computer simulations of cycling of this model to optimize for the proportional and integral controller gains. Finally, we implemented the optimized feedback controller into the microcontroller to test its performance in actually controlling the power output in outdoor cycling.

2.3 Methods

2.3.1 Identifying Cyclist Dynamics

To understand the cyclist's behavior, we first identified the dynamic relationship between the commanded cadence as an input and the power output. A participant completed two trials of 20 minutes cycling on an outdoor bike during which a metronome prompted pseudo-random step changes in cadence. We considered the participant as a dynamic system that can be experimentally identified by providing controlled inputs (commanded cadence) to the system and measuring its dynamic response (actual power). The step changes were $\pm 5\%$ and $\pm 10\%$ of their preferred cadence for a duration of 60 s each. A microcontroller (Teensy 3.1, Pjrccom Llc) controlled the metronome frequency of the participant's earphones. It also recorded the torque and angular velocity from a powermeter (Dura-Ace, SRM GmbH) and calculated the applied power twice per crank revolution. We modeled the system as forces acting on a point-mass m. *Please refer to Appendix A for more details about the different equation development steps.* We assumed the sum of the forces to be the horizontal forward force of the cyclist with the bike $F_{cyclist}$ and some counteracting air resistance force F_{drag}. By using Newton's second law, with $\dot{v}$ being the rate of change of the cyclist's speed, we formulated the following equation to describe the cyclist's motion:

$$F_{inertial} = -m\dot{v} = F_{cyclist} - F_{drag} \tag{2.1}$$

By assuming the force applied from the cyclist on the pedal to be representative of $F_cyclist$ and multiplying the forces with the respective velocities at their points of application, we then derived an equation that describes the mechanical power $P_{cyclist}$ generated at the pedals as a sum of the inertial and the drag power. The drag component P_{drag} represents the power that the cyclist must apply to overcome drag, whereas the inertial component $P_{inertial}$ represents the power the cyclist has to apply when accelerating.

$$P_{cyclist} = P_{drag} - P_{inertial} \tag{2.2}$$

We then expressed $P_{inertial}$ and P_{drag} as a function of the radius of the rear wheel r_{rw}, the length of the pedal crank arm l_p, the gear ratio GR, the speed v, the acceleration $\dot{v}$, and the drag number c:

$$P_{cyclist}(t) = \frac{r_{rw}}{l_p} \cdot GR \cdot m \cdot v(t) \cdot \dot{v}(t) + c \cdot \frac{r_{rw}}{l_p} \cdot GR \cdot v^3(t) \tag{2.3}$$

We calculated speed as a function of cadence, f, measured in revolutions per minute:

$$v(t) = \frac{1}{60} 2\pi \cdot r_{rw} \cdot GR \cdot f(t) \tag{2.4}$$

We took the derivative of v with respect to time t to get $\dot{v}$ and by substituting for v and $\dot{v}$ into equation 2.3, we determined the power as a function of cadence:

$$P_{cyclist}(t) = \frac{4\pi^2 m \cdot GR^3 \cdot r_{rw}^3}{60^2 \cdot l_p} \cdot \dot{f}(t) \cdot f(t) + c \cdot \frac{8\pi^3 \cdot GR^4 \cdot r_{rw}^4}{60^3 \cdot l_p} \cdot f^3(t) \tag{2.5}$$

The only unknown in this equation was the drag number c. We used a Levenberg-Marquardt optimization algorithm, implemented in Matlab's nlinfit function (The MathWorks, Inc., Natick, USA), to estimate the drag number that best fits the predicted power to the actual power. To evaluate the accuracy of the model, we determined the average absolute pacing error between the predicted and the actual power of the whole trial. We then defined the time delay t_d between the commanded and the actual cadence, to get an equation that describes $P_{cyclist}$ as a function of commanded cadence $f(t - t_d)$:

$$P_{cyclist}(t) = \frac{4\pi^2 m \cdot GR^3 \cdot r_{rw}^3}{60^2 \cdot l_p} \cdot \dot{f}(t-t_d) \cdot f(t-t_d) + c \cdot \frac{8\pi^3 \cdot GR^4 \cdot r_{rw}^4}{60^3 \cdot l_p} \cdot f^3(t-t_d) \tag{2.6}$$

In search for the time delay that best matched the actual cadence to the commanded cadence, we normalized all step changes to -1 before and 0 after the step change, and searched for the transfer function of the step changes with the commanded cadence being the input and the actual cadence being the output. The transfer function fits the modeled output to the measured output given the same input data [28].

2.3.2 Design of Feedback Controller

We used the mathematical model in a simulation of a closed-loop feedback controller. Equation 2.6 replaced the cyclist's dynamic relationship between the commanded cadence of the metronome and the actual power. We used a control algorithm in Simulink (The MathWorks, Inc, Natick, USA)to minimize the error between the target and the actual power, by adjusting the commanded cadence for the model of the cyclist. We used a discrete solver with a fixed-step size of 1, for which each time step represents one crank revolution. To determine the commanded cadence, we used a PI (Proportional Integral) controller. The PI controller measured the error between the target and the actual power and calculated the change in commanded cadence as a weighed sum of a signal proportional to the error (k_p), and a signal proportional to the integral of this error (k_i).

We then used the feedback controller simulation to optimize for the proportional and integral gains. The target power was step changes of +10% of the participant's preferred power with each step change lasting for around 60 s and the feedback controller tried to minimize the error between the target power and the actual power. To find the best combination of gains, we employed a brute-force search. We created a grid of values between 0 and 0.05 with a resolution of 0.002 to generate 26 values per gain. We chose this range based on prior tests. We ran the feedback simulation with all 676 combinations and quantified the performance using accuracy and responsiveness. For accuracy, we calculated the average absolute pacing error between the target power and the actual power during the last 30 s of each step, and the pacing variability, calculated as the coefficient of variation, during the same time period (Figure 2.1b). We quantified responsiveness as the response time, defined as the required time for the actual power to reach 95% of the target power following changes in target power, which was calculated by fitting a single exponential to each response and multiplying the resulting time constant by three (Figure 2.1a).

2.3.3 Testing of Feedback Controller

We tested the performance of the feedback controller using the optimized gains in outdoor cycling. To do so, a participant completed two trials of 16 minutes, during which they were guided through a range of target powers. The target power consisted of step changes of $\pm 7.5\%$ and $\pm 15\%$ of their preferred power. The microcontroller measured the error between the target and the actual power twice per crank revolution, calculated the change in cadence to minimize this error based on the proportional and integral gains, and adjusted the commanded cadence in real-time via a metronome (Figure 2.2). To evaluate the performance of the control system, we again quantified accuracy and responsiveness as described in 2.3.2.

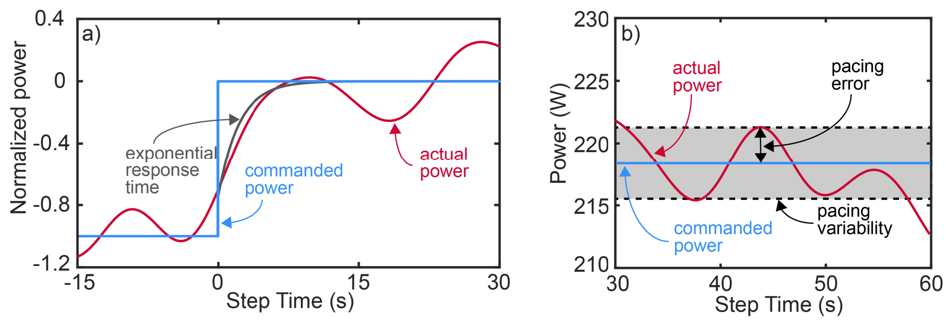

Figure 2.1: We calculated responsiveness as three times the time constant of the single exponential (a). The average absolute pacing error was the difference between the target power and the actual power, and the variability was the coefficient of variation within the last 30 s of each step (b).

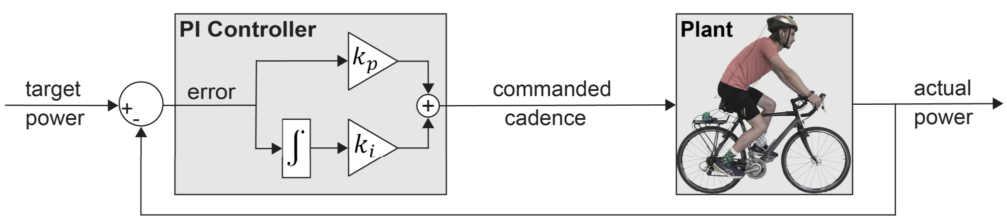

Figure 2.2: A closed-loop feedback system measures the error between the target and the actual power. Based on the error, a PI controller adjusts the commanded cadence. The plant (cyclist or model of cyclist) receives this change in commanded cadence and adapts the actual cadence. A change in cadence induces a change in actual power, which closes the feedback-loop.

2.4 Results

2.4.1 Identifying Cyclist Dynamics

The estimated drag number well fit our modeled data to the measured data. The fitted value for c was 0.36 ± 0.004. Pilot data are shown in Figure 2.3. The average absolute difference between the predicted power and the actual power was $15.9 \pm 11.7\%$ or about 37 W. The time delay was 1.8 data points or approximately one revolution of the crank.

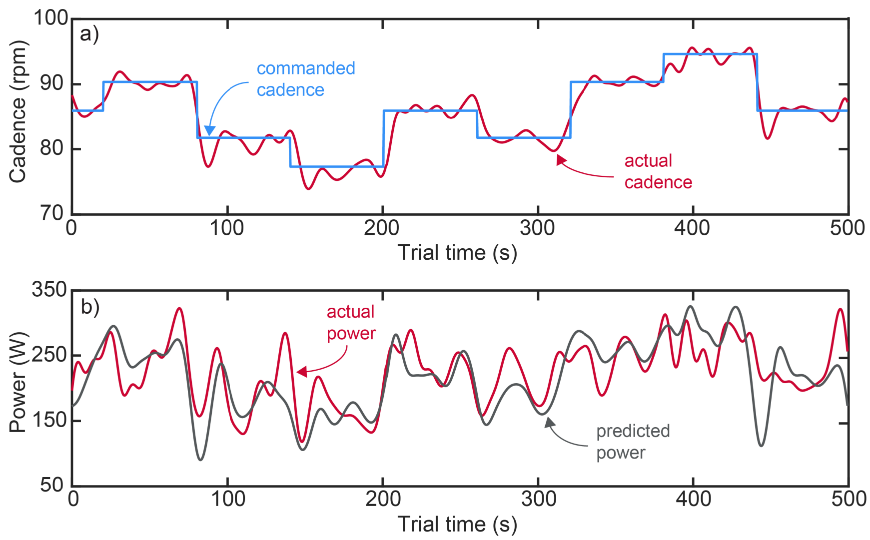

Figure 2.3: In the open-loop experiment, the participant had to follow step changes in commanded cadence (a). We measured the actual mechanical power of the trial and predicted the power with a mathematical model (b).

2.4.2 Design of Feedback Controller

In simulations, the optimized controller gains enabled rapid and accurate controller performance. The brute force search suggested values of 0.012 and 0.02 for the proportional and the integral gain, respectively. The average absolute pacing error between the target and the actual power during the last 30s of the target power was $< 0.01\%$ and the variability in actual power during this time period, calculated as the coefficient of variation, was 0.1%. The response time was 23.1s.

2.4.3 Real-time Controller

Optimized controller gains in outdoor experiments obtained accurate and responsive feedback control. Figure 2.4 shows pilot data of the outdoor controller. The average absolute pacing error between the target power and the actual power during the last 30 seconds of the target power was 3.2 ± 1.2% or about 7.6 W. The variability in power, calculated as the coefficient of variation during the same time period, was 2.9 ± 1.3% or about 6.8 W. The response time was 7.4±2.0 s.

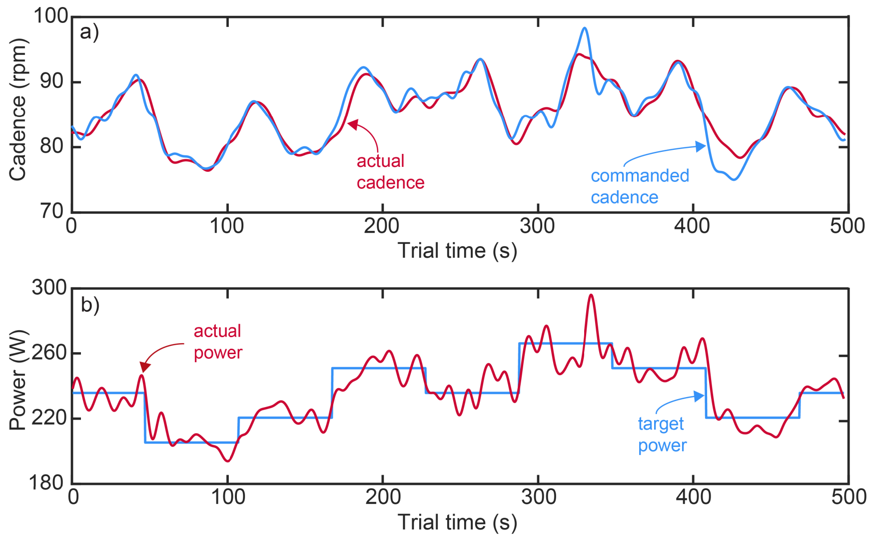

Figure 2.4: In the closed-loop experiment, the participant was asked to match the actual power to step changes in target power (b). To succeed, the participant had to change the actual cadence based on the constantly adjusted commanded cadence calculated from the feedback controller, and communicated via a metronome in the participant's earphones (a).

2.5 Discussion

This paper presents our approach to develop a novel system to control mechanical power in cycling. To understand the cyclist's dynamic behavior, we first developed a mathematical model that can predict the mechanical power output following changes in cadence. With this model, we performed simulations to optimize the design of a closed-loop feedback control system that controlled power by changing the cadence. We optimized for the proportional and integral controller gains of the controller and then used these gains to test the performance of the actual feedback controller in outdoor cycling where a participant was guided through a range of target powers and the feedback controller adjusted the cyclist's power accordingly with a metronome.

Our mathematical model estimated a realistic c value, but we will further leverage the model for higher accuracy. Our c can be defined by the drag area C_dA and the air density ρ:

$$c = \frac{1}{2} C_d A \rho \tag{2.7}$$

For an air density of 1.23-1.25 kg/m^2 and a drag area of 0.27-0.36 m^2 for an upright position [57, 107, 130] c would be between 0.17 and 0.23. With a value of 0.36 our c was slightly larger. We expected a larger value, because our drag parameter subsumes all unmodeled losses, such as rolling resistance or wind direction. For higher accuracy between the predicted and the actual power, we will further refine our model. This might include adding measurements of the rolling resistance, the wind strength and direction, or other parameters.

Accuracy was better in the simulations, but responsiveness was better in outdoor experiments. We expected better performance in accuracy in simulations than in outdoor experiments for several reasons. First, our mathematical model does not perfectly represent the cyclist. We did not include any measurement noise, participant noise, or disturbances to our model, which contributes to a larger pacing error and variability in cycling. Since we did not include a derivative gain to our control system, which is a gain that is very sensitive to measurement noise, it was not crucial for us to include noise to our simulation. Second, we optimized for the best gains for the model and not for the cyclist. We then transferred these gains to the cyclist, which might have a different gain optimum. Response time of the outdoor experiment was about a third of the responsiveness of the simulation. This discrepancy can again be explained by an imperfect simulation, but we will have to more closely investigate the model.

It is unclear whether our feedback control system led to an increase in performance. Literature is limited on data in cycling pacing accuracy. Mauger et al. found pacing errors of 2.5% and a coefficient of variation of around 3.5% when giving timing feedback [130]. A pacing error of 3.2% and a coefficient of variation of 2.9% in our study does not indicate a performance improvement. To better quantify the performance differences between using and not using our feedback system, we will conduct our own experiment, comparing cycling that is self-paced, with cycling with a monitor that displays the power, and with cycling with our feedback system.

Our approach has several limitations. First, our model is just an approximation of the cyclist's dynamic behavior. This leads to discrepancies between the feedback control simulations and the outdoor experiments with the feedback controller. To minimize these discrepancies, we will have to more closely investigate our mathematical model, to understand its limitations and improve its performance. Second, the results shown in this paper are from a pilot study with one participant, which adds uncertainty to the results presented. Third, we used one gear ratio for the whole study, determined by the participant before the first experiment. The mathematical model accounts for the gear ratio but we have not yet investigated if changing gear ratio will change the accuracy of our model and if it affects the performance of the closed-loop feedback controller.

Our next steps will be to improve this control system to provide cyclists with high performance feedback. Towards this goal, we will fine tune our mathematical model using data from more cyclists and using a larger number of gear ratios. This system will provide cyclists with stroke by stroke control over their power. Athletes, or their coaches, will be able to set and complete different training protocols, such as interval training, with high accuracy, and hence, improve their performance.

Chapter 3

Comparing the advantages and disadvantages of physics-based and neural network-based modelling for predicting cycling power

3.1 Abstract

Models of physical phenomena can be developed using two distinct approaches: using expert knowledge of the underlying physical principles, or using experimental data to train a neural network. Here, our aim was to better understand the advantages and disadvantages of these two approaches. We chose to model cycling power because the physical principles are already well understood. Nine participants followed changes in cycling cadence transmitted through a metronome via earphones and we measured their cadence and power. We then developed and trained a physics-based model and a simple neural network model, where both models had cadence, derivative of cadence, and gear ratio as input, and power as output. We found no significant differences in the prediction performance between the models. The advantages of the neural network model were that, for similar performance, it did not require an understanding of the underlying principles of cycling nor did it require measurements of fixed parameters such as system weight or wheel size. These same features also give the physics-based model the advantage of interpretability, which can be important when scientists want to better understand the process being modelled.

3.2 Commentary

This chapter uses a slightly different physics-based model from Chapter 2. At the end of this chapter, I will compare the two models, and explain why they had similar performance during the model optimization, even though the optimized drag parameters c were different.

In Chapter 2 we also used the model to optimize for feedback controller settings. I will also compare the differences in these optimizations, and explain why they led to similar results.

3.3 Introduction

Models are useful. Using models, scientists can better understand and prevent injuries [69, 103, 8, 218, 18, 216]. Models can give insights into how muscles work [95, 234, 191, 82, 204] and help define human limits to develop anti-doping tools [153, 67, 188]. They can also simulate variables that are hard or expensive to measure. In cycling, for example, devices use models to estimate the mechanical power output of riders. This is useful for riders who do not own equipment that can measure mechanical power directly.

Developing these models from first principles can be difficult. Scientists design models to describe the real-world relationships that transform independent variables into the dependent variables. One option to model this input-output relationship is to understand and apply the principles underlying a particular process. For example, developing a physics-based model for cycling that can predict mechanical power (the output variable) requires first identifying the input variables that affect the power—such as speed or drag forces—and then identifying the parameters and how they are combined with the input variables to predict the output variable [128]. These parameters can be identified through measurements, or from data [53]. Using this physics-based approach to develop models has at least two major challenges. First, this process can require a detailed understanding of the principles underlying a process, which may be unknown or complex. Second, real-world measurements introduce inaccuracies, which stem from equipment measurement errors, and the fact that nothing can be measured perfectly. Inaccurately measured parameters can subsequently reduce the performance of the overall model. For example, to predict cycling speed from cadence a scientist would have to first understand the underlying principles of how the angular velocity of the pedal translates to the linear velocity of the wheel, and second to measure bike parameters such as the wheel radius.

Data-driven neural networks can assist the process of developing models. Neural networks are named as such because they loosely imitate the human brain. Mathematically, they consist of a set of functions that can be trained with data to recognize patterns in complex data sets. Because neural networks can learn from data, there are many applications for which they can be used. Modelling the input-output relationship of processes with neural networks still requires knowledge about the input variables. But, given enough data, neural networks can approximate a wide variety of input-output relationships without explicitly having to measure many relevant fixed parameters, or understand the principles underlying a process, ameliorating the two challenges identified above [98]. For example, to predict cycling speed from cadence a neural network could learn the relationship between the cadence and the cycling speed without understanding the principles that relate speed and drag to power, and without requiring measurements of the bike parameters such as the wheel radius.

In order to better understand the advantages and disadvantages of developing models using a first principles or data-driven approach, here we compare a physics-based model for predicting mechanical power in cycling with a predictive model developed using neural networks. We chose cycling for two reasons. First, the underlying principles upon which to build a physics-based model are well-understood [128, 127, 56, 72]. Second, there is both scientific and commercial interest in accurately predicting mechanical power during cycling. Scientifically, it can help to better simulate racing strategies [53, 72, 83, 251]. Commercially, this knowledge can lead to products that help athletes to indirectly measure their power without the necessity of expensive power metres. To accomplish our goal, we first built a microcontroller-operated system that provides the cyclists with metronome-indicated changes in cadence and measures the power output. We used this system to measure cyclists' power output during two trials of cycling on a flat running track with two different gear ratios while following step changes in commanded cadence. Using this data, we developed and parameterized a physics-based model and a neural network model that best fit the simulated power to the measured power. We then compared how accurately these two models predicted the measured mechanical power, and evaluated the advantages and disadvantages of each approach.

3.4 Methods

3.4.1 Data Collection

We tested nine participants in this experiment (3 females and 6 males; body mass: 72.2 ± 9.4 kg; height: 177.2 ± 10.5 cm; age: 28 ± 5 years; mean ± std). The Office of Research Ethics at Simon Fraser University approved the study (#20180650). All participants provided written and verbal informed consent before participating in our study.

During the experiment, participants cycled on a 400 m running track. All participants used the same bike (Specialized Tricross Comp Size 52, Specialized Bicycle Components, Inc.) and adjusted the seat height to their own preference. During cycling, they carried a backpack with a microcontroller (Teensy 3.1, Pjrccom Llc.). The microcontroller measured torque in the pedal crank arm continuously from an SRM power metre (Dura-Ace, SRM GmbH). Twice per crank arm revolution (every half pedal stroke), the microcontroller measured the crank arm angular velocity using a reed switch, and calculated the mechanical power by multiplying the time-averaged torque with the angular velocity:

$$P_P = \tau_p \cdot \omega_p \tag{3.1}$$

As a warm-up and to familiarise participants with the bike, we first instructed them to cycle at a comfortable speed for 5-10 minutes. During this familiarisation period, participants chose their preferred rear gear (16.5 ± 0.5 teeth), while we kept the front gear fixed (39 teeth). We measured their preferred cadence (67 ± 12 rpm) as the average cadence during a 30 second period towards the end of the familiarisation period. Next, participants completed an 18 minute trial with the rear gear being one gear over their preferred rear gear. This was followed by a second 18 minute trial with the rear gear one gear under their preferred rear gear. We instructed participants to keep their body position (i.e., high vs. low handlebar position) the same throughout the experiment to keep their frontal area, which affects the drag, relatively constant. A metronome, controlled by the microcontroller and communicated to the participant through earphones, commanded step changes of ±5%, ±10%, and ±20% of the participant's preferred cadence, centred about the preferred cadence (Figure 3.1). We instructed participants to match the metronome beat as accurately as possible with their cadence. Step changes occurred every 60 s and participants could rest for 10 mins between the two trials.

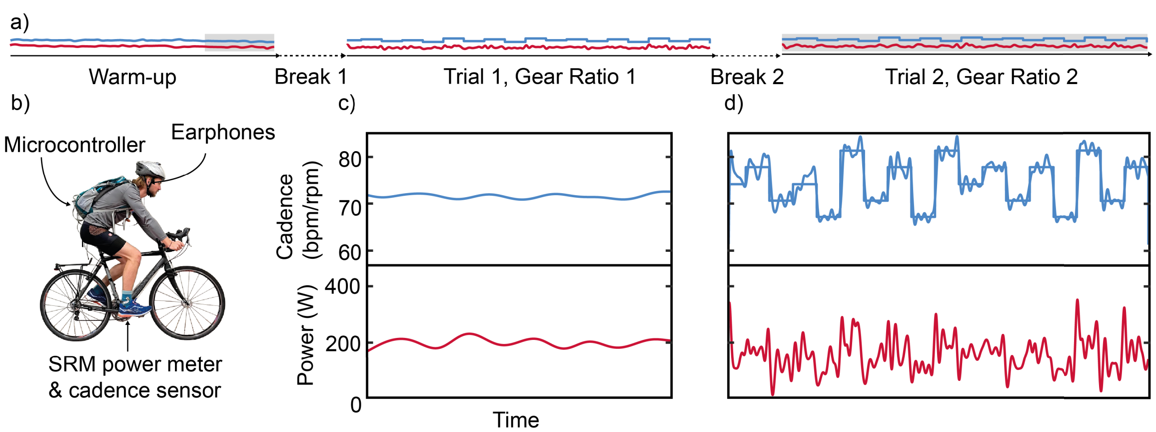

Figure 3.1: The experimental setup. a) illustrates the timeline of the experiment with the Warm-up, during which we evaluated the participant's preferred cadence (grey box), Break 1, Trial 1 with Gear Ratio 1, Break 2, and Trial 2, with Gear Ratio 2. b) illustrates the participant with the equipment. c) magnifies the data in the grey box of the warm-up. d) magnifies the data in the grey box of trial 2. Metronome cadence is measured in beats per minute (bpm), cycling cadence is measured in revolutions per minute (rpm), and power is measured in Watts.

3.4.2 Development of the Physics-based Model

To derive an expression for the mechanical output power of the cyclist as a function of the input cadence and gear ratio of the cyclist we model the system as horizontal forces acting on a point mass (m). One force is applied by the bike's rear wheel (F_{rw}), and a counteracting force is applied by air resistance (F_{drag}). Using Newton's second law to describe the cyclist's motion yields:

$$m\dot{v} = F_{rw} - F_{drag} \tag{3.2}$$

where $\dot{v}$ is the rate of change of the cyclist's speed. F_{drag} is dependent on the squared speed (v^2), the air density (ρ), the frontal area of the cyclist (A), and the drag coefficient (C_d) [26]:

$$F_{drag} = \frac{1}{2}AC_d\rho v^2 \tag{3.3}$$

Due to multiple reasons, we replaced all but the squared velocity with one single variable which we call the drag number (c). First, we did not measure frontal area or air density. Second, our drag number is not only air drag but subsumes all other factors of drag, such as rolling resistance. Isolating F_{rw} in equation 3.2, and substituting the product of the squared speed and the drag number for F_{drag}, yields:

$$F_{rw} = m\dot{v} + cv^2 \tag{3.4}$$

Using the forces and radii in Figure 3.2 to calculate the transformation of force from the pedal to the rear wheel yields:

$$F_{rw} = F_p \cdot \frac{r_{rg}}{r_{rw}} \cdot \frac{r_p}{r_{fg}} \tag{3.5}$$

Replacing F_p with the ratio between the torque generated by the user on the crank arm (τ_p) and the pedal length (r_p) and the ratio between the front gear radius (r_{fg}) and the rear gear radius (r_{rg}) with the gear ratio (GR) yields:

$$F_{rw} = \frac{\tau_p}{GR \cdot r_{rw}} \tag{3.6}$$

Substituting this expression for F_{rw} into equation 3.5 yields:

$$\frac{\tau_p}{GR \cdot r_{rw}} = m\dot{v} + cv^2 \tag{3.7}$$

Multiplying both sides with the gear ratio, the rear wheel radius, and the pedal's angular velocity yields the mechanical power applied by the cyclist (P_p) on the left side of the equation:

$$P_p = \omega_p GR r_{rw} m\dot{v} + \omega_p GR r_{rw} cv^2 \tag{3.8}$$

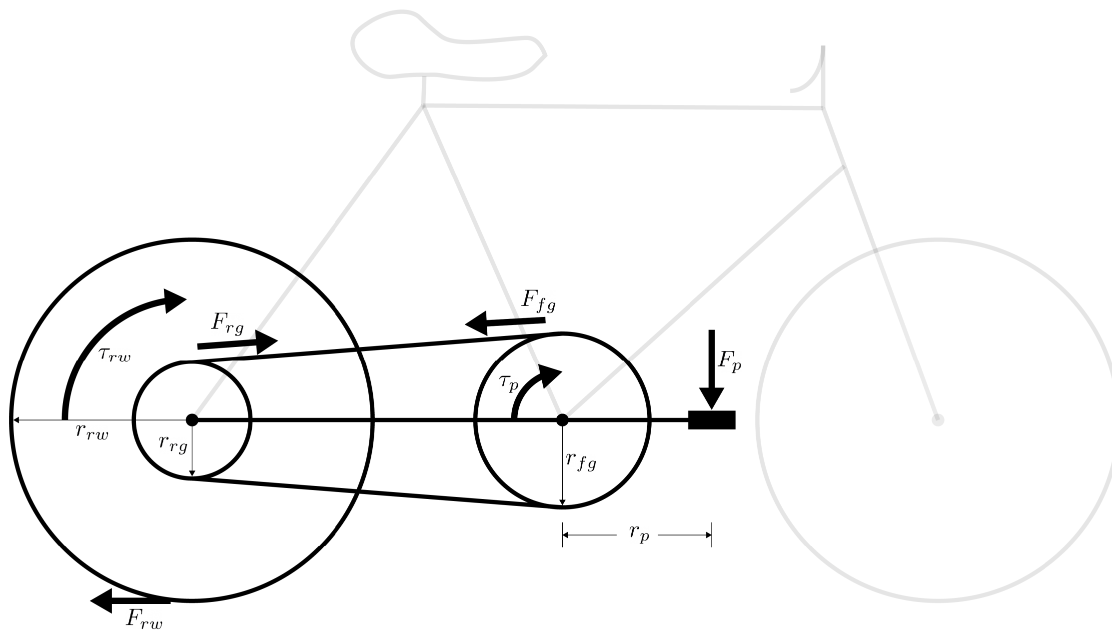

Figure 3.2: Illustrates the relevant forces (F), radii (R), and torques (τ) in the pedal, front gear, rear gear, and rear wheel.

The angular velocity in the pedal is equal to the ratio between the angular velocity in the rear wheel and the gear ratio, and the angular velocity in the rear wheel equals the linear velocity of the cyclist and the radius of the rear wheel, yielding:

$$\omega_p = \frac{\frac{v}{r_{rw}}}{GR} \tag{3.9}$$

Substituting this expression for ω_p into equation 3.8 simplifies that equation to:

$$P_p = mv\dot{v} + cv^3 \tag{3.10}$$

Expressing speed as a function of the measured gear ratio and the measured cadence (f) yields:

$$v = \frac{2\pi r_{rw} \cdot GR \cdot f}{60} \tag{3.11}$$

Substituting this expression for v into equation 3.9 and simplifying yields:

$$P_p = \frac{m\pi^2 r_{rw}^2}{90} GR^2 f\dot{f} + \frac{2c\pi^3 r_{rw}^3}{15} GR^3 f^3 \tag{3.12}$$

where $\dot{f}$ is the rate of change of the cadence. This equation expresses the output mechanical power of a cyclist as a function of the measured time-varying cadence and the experimentally-manipulated gear ratio. The only unknown and optimizable parameter is the drag number c — all other parameters in the equation can be measured (Table 3.1).

Table 3.1: Values of all measurable parameters of the physics-based model.

Parameters	
r_{rw}	0.30 m
r_p	0.17 m
m	72.2±9.4 kg (participant weight) + 13.0 kg (bike and equipment weight)
GR	2.4±0.2

To optimise for a drag number that best fit the predicted power to the measured power, we used a Levenberg-Marquardt optimization algorithm, implemented in Matlab's nlinfit function (R2020a, The MathWorks, Inc., Natick, USA) [205].

3.4.3 Development of a Neural Network Model

When developing a neural network, there are many choices to make about the architecture of the network. These choices include the structure of the data that is input into the network, types of network layers, the number of layers, the number of nodes per layer, and the type of activation function applied to each layer's output. While there are no clear rules to specify network architecture to maximise model performance on a given problem [71, 104], there are certain architectures that have historically performed better on some problems than others. We used historical performance as well as pilot analyses to guide the following choices:

Data structure: To predict power for each half pedal stroke, we used input data from that half pedal stroke as well as the seven previous half pedal strokes. For all models, the input data at each half pedal stroke included the cadence and the derivative of cadence. For some models, the input data also included gear ratio (Figure 3.3). We chose time windows of eight half pedal strokes because longer windows required greater computational power and pilot analyses revealed good performance with our chosen window length.

Types of layers. We chose to use recurrent layers which are comprised of nodes whose output can affect the next input to nodes of the same layer. They often perform better with temporal tasks—tasks where the data changes over time—because they can store information from past data. More specifically, we used long-short-term-memory layers, which can further improve the performance over other types of recurrent layers, by prioritising which information from past data to store [116].

Number of layers. There are different advantages and disadvantages for both shallow neural networks (one hidden layer only) and deep neural networks (two or more hidden layers) [27, 148, 2, 110]. For simplicity, and because pilot analyses showed good performance, we chose to use only one hidden layer.

Number of nodes per layer. In pilot experiments, we found similar performance for a small number of layer nodes [234] when compared with greater numbers of nodes (16, 24,..., and 1024). For simplicity, we chose to use 8 nodes.

Activation function. Typically, each layer in a neural network is followed by an activation function, which transforms the output of each node in the layer and provides the network with non-linear modelling capabilities. Due to their widespread success in deep neural networks, we used a rectified linear unit (ReLU) as activation functions for the long-short-term-memory layer [195, 210]:

$$f(x) = max(0, x) \tag{3.13}$$

A ReLU activation function deactivates nodes with an output of smaller than 0, giving them the advantage of turning individual nodes on and off. We did not include additional activation functions for the output layer, because pilot analyses revealed better performance without output layer activation functions when compared with a ReLU activation function.

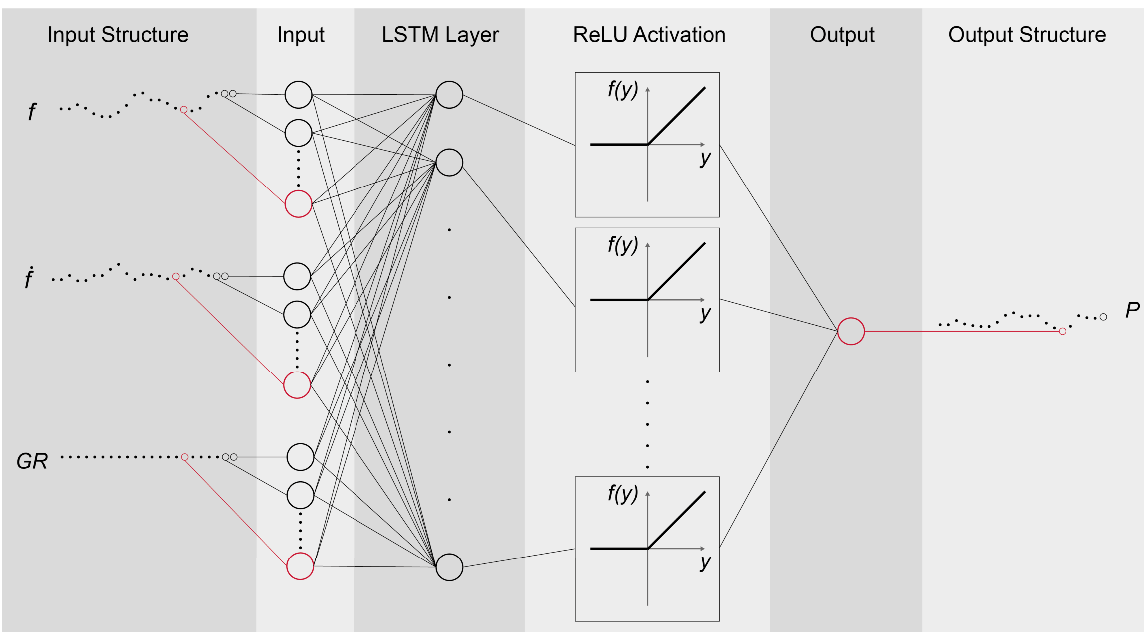

Figure 3.3: Illustration of a conceptual model of the neural network from input structure to output structure. Notice that for illustration purposes the data structure of the input and output are illustrated with the time evolving from right to left. To predict one output datapoint (power P) on the right (output structure), eight input time steps per input (cadence f, cadence derivative $\dot{f}$, and gear ratio GR) are required. The red dots in the input structure illustrate the eighth and last input datapoint, and the red dot in the output structure illustrates the eighth output datapoint, which is the datapoint the neural network is predicting.

3.4.4 Data Analysis

To better determine the advantages and disadvantages of the physics-based and neural network models, we performed two analyses: a within-trial analysis and a within-participant analysis. First, we tested the prediction performance within each trial. Here the models' aim was to learn from parts of the data within a trial and predict the rest of the data within the same trial. The neural network's input was the cadence and the derivative of the cadence and did not require knowledge of the gear ratio, as it was a fixed parameter. Second, we tested the prediction performance within each participant. Here, the models' aim was to learn from parts of both trials and predict the rest of the data within the same participant. Here, the neural network required knowledge of the gear ratio as an additional input, as it was a variable that was different between the two trials.

We used normalised root mean square error, k-fold cross validation, and paired t-tests to compare model performance. To test the prediction performance, we calculated the normalised root mean square error, where we normalised the root mean square error by the mean of the measured data. Additionally, we also calculated the normalised mean error, where we normalised the mean error by the mean of the measured data. We split up each participant's trial into three subsets, also called folds (Figure 3.4). To test the performance of the physics-based model and the neural network model in the within-trial experiment we trained the models with two of the subsets within a trial and tested the accuracy of predicting the power with the third, using both the normalised root mean square error and normalised mean error. For example, we would use fold 1a and fold 1b to train the model and fold 1c to test the prediction accuracy. Here, we did 3-fold cross validation: We used each of the three subsets as a test set once to get the prediction accuracy three times. To test the performance in the within-participant experiment, we trained the models with five of a participant's subsets and tested the accuracy of predicting the power on the sixth. For example, we would use fold 1a, fold 1b, fold 1c, fold 2a, and fold 2b to train the model and fold 2c to test the prediction accuracy. Here we did 6-fold cross validation: We used each of the six subsets as a test set once to calculate the prediction accuracy six times. To compare overall performance, we averaged the normalised root mean square errors of each participant and compared the mean normalised root mean square error between the physics-based model and the neural network model with a paired t-test using a significance level of $p < 0.05$.

3.5 Results

The physics-based model and the neural network model had similar predictive performance. The normalised mean error and normalised root mean square error for the within-trial analysis — in which the different gear ratio trials were kept separate when we trained and tested the model — of the physics-based model were 1.6%±1.1% and 19.6±5.1%, respectively

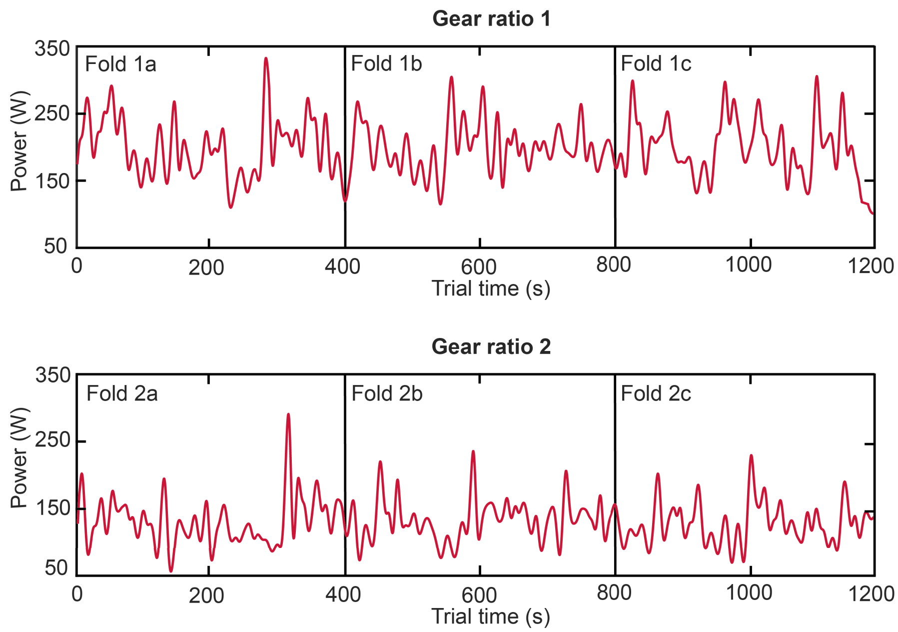

Figure 3.4: Illustrates the two trials with different gear ratios, and the subsets within each trial for the within-trial and within-participant analysis.

(mean between participants ± standard deviation between participants; Figure 3.5). With this predictive performance, we expect a new participant with a measured average power output of 300 W to have a predicted average power that is 5 Watts (1.6%) above the actual average power. And for 95% of the half pedal strokes at 300 W, we expect the predicted power for this new participant to be within 116 Watts (19.6%*1.96). On average, the optimised drag number was 1.2±0.2. The normalised mean error and normalised root mean square error for the within-trial experiment of the neural network model were 1.2%±4.2% and 18.2±6.0%, respectively (Figure 5). The predictive performance between the two models was not significantly different (p = 0.34).

The normalised mean error and normalised root mean square error for the within-participant analysis — in which we combined the different gear ratio trials when we trained and tested the model — of the physics-based model were 3.2% ± 1.8% and 20.9±5.1%, respectively (Figure 3.6). On average, the optimised drag coefficient was again 1.2 ± 0.2. The normalised mean error and normalised root mean square error for the within-participant experiment of the neural network model were 4.1%±10.9% and 25.4±5.6%, respectively (Figure 6). Again, the predictive performance between the two models was not significantly different (p = 0.12).

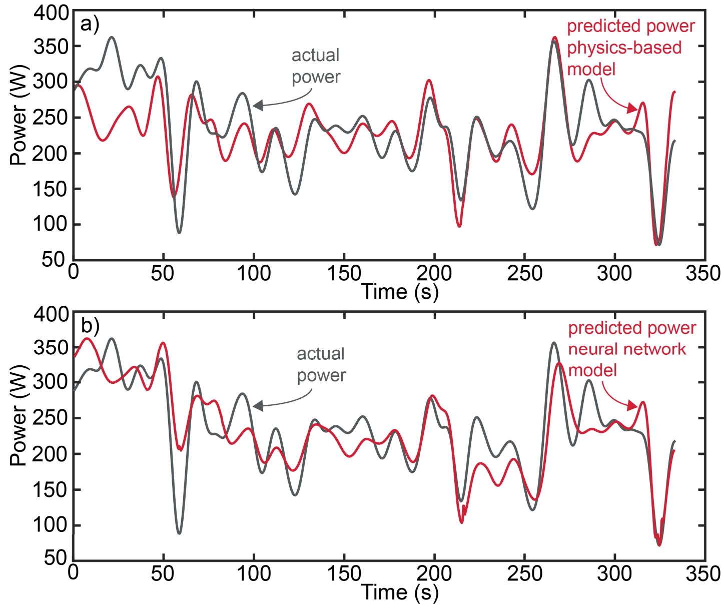

Figure 3.5: Representative prediction data for the within-trial analysis. These representative trials had similar RMSEs and normalised mean errors with the overall average.

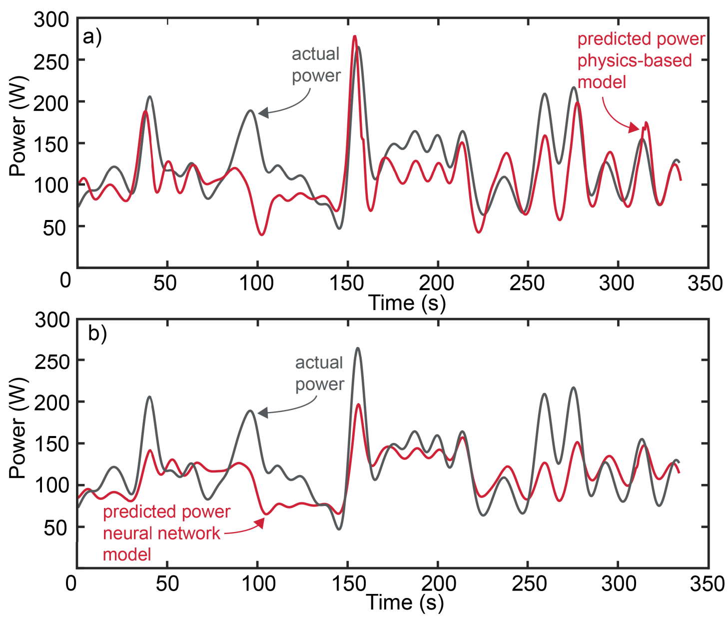

Figure 3.6: Representative prediction data for the within-participant analysis. These representative trials had similar RMSEs and normalised mean errors with the overall average.

3.6 Discussion

Here we developed and compared a physics-based model and a neural network model in predicting cycling power from changes in cadence and gear ratio. We chose cycling because its physics are well understood. In our physics-based model, we optimised for the only unknown, the drag number. For the neural network model, we used a simple recurrent neural network with one long-short-term-memory layer consisting of eight nodes. We found that the neural network model had a similar performance to that of the physics-based model.

Neural networks can help develop models when we do not understand the underlying principles of a problem. To develop the physics-based model we needed an understanding of the underlying principles of cycling. In comparison, the neural network could automatically learn the input-output relationship. If we would decide to add new input variables to the model, like for example continuous wind speed and direction, we suspect it would be easier for a scientist without an understanding of the underlying principles to train a new neural network with the added variables, than to find the correct way to add these variables to the physics-based model. Furthermore, a scientist with sufficient expertise in neural network modelling is well poised to develop new models for many other physical phenomena, without being an expert in the underlying principles of any of the systems. These are advantages of modelling using neural networks over physics-based modelling.

The physics-based model had more physically-meaningful parameters, introducing both advantages and disadvantages. For the physics-based model we used measured parameters, such as the rear wheel radius and the participant's weight. We did not measure these parameters for the neural network, removing an extra step and potential for inaccuracies. But having fixed parameters makes it easier for future changes in the experimental environment. For example, if we decided to change the bike, the physics-based model would only need the new rear wheel radius and weight of the new bike, but the neural network would need new training with the new information. Having fixed physical parameters in the physics-based model also makes it more interpretable, which can help better understand the performance of a model, and subsequently increase the fundamental understanding of the particular problem itself. A neural network creates its own representation of a problem, which makes it harder to interpret.

Others have also shown the utility of neural networks when developing models of complex dynamic systems. Some have shown how to combine physics-based models with neural network models to enhance performance [226, 55, 224, 34]. Others have directly compared physics-based models and neural network models, similar to our project. For example, Choi et al. [42] compared the design and implementation of a physics-based model and neural network models for predicting the performance of a cooling system of a gasoline vehicle equipped with an electric control valve. Hu et al. [102] compared the design and implementation of a physics-based model, a combination of physics-based and neural network model, and a direct neural network model for simulating different metrics in a diesel combustion engine. In both cases, their findings suggest that developing the neural network required less expert knowledge and took significantly less time. In a complex process like this, expert knowledge is not only required to develop the physics-based model, but also to get valid measurements for the model's parameters. Correspondingly, the authors found highest prediction accuracy with the neural network model. Such as in our project, they also see advantages in using physics-based models, such as better interpretability and better durability against the worst anomalous conditions in which there is not enough data for the neural network to learn accurately.

In our study, both models converged to similar, but not perfect, prediction accuracies. We expected this imperfect performance as there are many variables in cycling that affect the power output that we did not include in our models as they would have required complex measurement systems [128]. For example, we did not measure or model headwinds or tailwinds which increase and decrease the drag force, respectively. Our participants cycled on an oval running track creating situations where in the presence of a prevailing wind, participants alternatively experienced headwinds and tailwinds with neither of these forces represented by changes in the inputs of the model. Incorporating continuous wind speed and direction could enhance the performance of both models. Doing so would be more difficult for the physics-based model, since we would have to understand how the wind speed and direction affects the whole system to properly add it to the model. In comparison, to add additional variables to the neural network model simply requires retraining the model with the added new variable in the input data. More generally, we suspect that as the complexity of the process to be modelled increases, or as the number of required measured inputs increases, a data-driven modelling approach will prove simpler, although harder to interpret, than a physical modelling approach.

3.7 Commentary

During the comparison, I will call the model from Chapter 2 the “original” model and the model from Chapter 3 the “updated” model.

3.7.1 Model Differences

Please refer to Appendix A for more details about the different equation development steps of the original model. In Chapter 2, for the original model, we modeled the system as forces acting on a point mass (m). One force is applied by the cyclist and a counteracting force is applied by air resistance (F_{drag}). Using Newton's second law to describe the cyclist's motion yields:

$$m\dot{v} = F_{cyclis} - F_{drag} \tag{3.14}$$

The fundamental difference to the updated model is that — instead of using the force at the rear wheel for the horizontal forward force — we assumed the force applied from the cyclist on the pedal to be representative of $F_{cyclist}$. We replaced $F_{cyclist}$ with the ratio of the torque in the pedal crank arm τ_p and the length of the pedal crank arm l_p, yielding:

$$\frac{\tau_p}{l_p} = m\dot{v} + F_{drag} \tag{3.15}$$

Because we described the horizontal force acting on m with the force acting on the pedal, this model leads to a slightly different and conceptually wrong model. Before describing the speed with cadence, our calculations then lead to this final equation, where $P_{cyclist}$ is the mechanical power applied by the cyclist, r_{rw} is the rear wheel radius, l_p is the pedal length, GR is the gear ratio, v is the speed, and $\dot{v}$ is the acceleration:

$$P_{cyclist} = \frac{r_{rw}}{l_p} \cdot GR \cdot m \cdot \dot{v} \cdot v + c \cdot \frac{r_{rw}}{l_p} \cdot GR \cdot v^3 \tag{3.16}$$

In Chapter 3, before describing the speed with the cadence we have equation 2.3. The only difference between the final two models is that the original model multiplies the drag and the inertial term with the factor $\frac{r_{rw}}{l_p} \cdot GR$.

3.7.2 Model Comparison - Drag Number Optimization

The updated model predicts the power slightly better than the original model with lower peaks. We found a drag number c of 0.3609 ± 0.0103 and 1.3101 ± 0.0225, and an nRMSE between the actual and predicted power of 20.80 ± 1.9092% and 18.62 ± 6.0528% for the original and updated model, respectively. The nRMSE between the two models was 15.52 ± 1.61%. Figure 3.7 shows example data on how the models performed when compared to the actual power. Because of the added $\frac{r_{rw}}{l_p} \cdot GR$ factor, the original model's peaks are higher, but the drag number is much smaller, when compared to the updated model. Let's consider the data from Figure 3.7, where $\frac{r_{rw}}{l_p} \cdot GR$ is equal to 3.6223. The peaks in the original model are higher, because the inertial part gets multiplied with this value, while the inertial part of updated model does not. In the drag part, the low drag number of the original model equalizes the effects of the $\frac{r_{rw}}{l_p} \cdot GR$ factor. The drag number was 0.3536 for this data. Multiplying this drag number with $\frac{r_{rw}}{l_p} \cdot GR$ results in 1.2808. This is very similar to the updated model's drag number 1.2942. Equation 3.17 shows this relationship.

$$c_{original} \approx c_{updated} \cdot \frac{r_{rw}}{l_p} GR \tag{3.17}$$

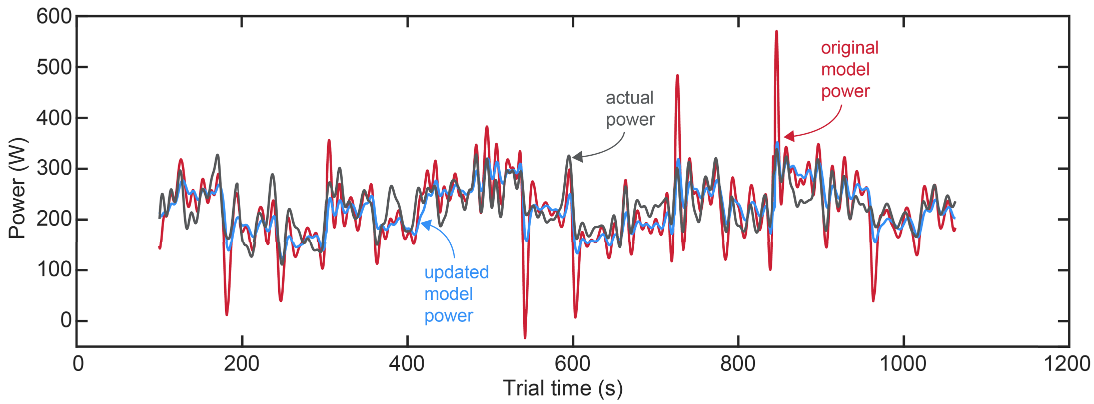

Figure 3.7: Illustrates the power predictions of the original model (red) and the updated model (blue) when compared to the actual power (grey) in one example trial.

3.7.3 Model Comparison - Feedback Controller Design

The controller gains determined from the original model work well for the updated model. In the original simulation from the original model in Chapter 2, the optimized controller gains were 0.012 and 0.02 for the k_p and the k_i, respectively. In an updated simulation with these gains, we found that the nRMSE between the target power and the simulated power were 5.88% and 3.16% for the original model and updated model, respectively. The updated model was therefore better in feedback control simulations, when using the optimized gains from the original model, than the original model itself, explaining why these gains worked well during outdoor experiments.

By optimizing for new controller gains with the updated model, the feedback controller in the simulation could improve. For the updated model, the optimization found a k_p and k_i of 0.024 and 0.03, respectively, with an nRMSE of 2.59%. The updated model could use higher and more aggressive gains. This is because, compared to the original model, changes in cadence would not lead to such rapid changes in power.

In conclusion, the feedback controller in our outdoor cycling experiment with optimized gains from the original, and conceptually wrong, model worked well for the following reasons. First, the gains from the optimization with the original model showed better feedback control in simulations with the updated model, which is a more realistic representation of the real dynamics. Second, the controller gains from the optimization with the original model were similar, but less aggressive, than the ones from the optimization with the updated model. Lower gains typically lead to slower, but stable feedback control. And third, models are always a simplified version from the real mechanisms, and for good dynamic control we often do not need highly accurate models [200].

Chapter 4

Running patterns can not be used to classify running performance.

4.1 Abstract

Athletes and coaches may seek to improve running performance through adjustments to their running pattern. Running patterns can distinguish individual runners as well as groups of runners, such as females and males, youth and elderly, or long-distance and short-distance runners. Yet, in long-distance running it is still unclear whether certain running patterns lead to better performance. In this study, we used a neural network to further test whether there is information available within individual running patterns to classify individual runners' long-distance running performance. To accomplish this, 119 participants reported their personal best 10 km run time. They ran on a treadmill at three different speeds and overground at a self-selected sub-maximal speed while we collected data from IMUs inserted in the insoles of both shoes. First, we trained the neural network to identify individual runners from their running data. Then, we trained the same neural network to classify the runners' performance. With enough data, the neural network was successful in identifying individual runners, but failed in classifying their running performance. We interpret the failure of the same model to classify running performance as evidence that individual running patterns measured from IMUs inserted in the shoe-insoles do not contain useful information about a runner's performance. We also showed that a neural network's capability of identifying individual running patterns does not scale with an increasing number of runners.

4.2 Introduction

Athletes and coaches may seek to improve running performance through adjustments to their running pattern. Part of the rationale for this belief is that running patterns distinguish individual runners as well as groups of runners. Every runner has an individual running pattern. Whether using 3D motion analysis data combined with force plate data [97], force plate data by itself [99], or IMUs mounted to both shanks [246], algorithms are able to detect individual runners' running patterns. Different groups of runners also demonstrate different running patterns. For example, runners of different sexes or different age groups have different running patterns [77, 182, 66]. When normalized for speed, there are differences between runners specialized in different distances [50, 179]. Running shoes also lead to shoe-specific running patterns [99]. Individual running patterns and group running patterns are not mutually exclusive. Horst et al. could distinguish individual running patterns, regardless of changing footwear, but also distinguish different footwear regardless of the runner [99].

Yet, whether certain running patterns, specifically in long-distance running, lead to better running performance is still unclear. In sprinting, better technique can improve performance [147]. In long-distance running, Moore concluded in a literature review that biomechanical variables during ground contact seemed to have the strongest association with running economy, but also acknowledged that there are still major shortcomings in the performed studies [154]. Since then, several studies have aimed to find evidence for a good running pattern. For example, Agresta et al. could not find any relation between years of running experience and motion analysis data [7]. Patoz et al. also found no running pattern that was connected to a better running economy [178]. Subjectively, even running coaches are unable to tell whether a specific running pattern is good or bad [48]. Conversely, Clermont et al. could distinguish between recreational and competitive runners with 3D motion analysis independently of their sex [46], as well as with IMU data collected at the center of motion between recreational and competitive runners when split up into their respective sexes [45]. This is not strong evidence. In both studies, the group used a cross-fold validation algorithm — which is when an algorithm trains with a predetermined dataset, tests its accuracy on a left-out dataset, and repeats the same process with changing training and test datasets —, but instead of leaving out a certain number of participants, they seemed to leave out a certain amount of data (i.e., 90% in [46] and 70% in [45]). This risks that the algorithm learns the association of a runner's running pattern with their running performance, instead of the general running pattern of a recreational or a competitive runner.

If there was a detectable difference in running patterns between high and low performance runners, neural networks might find pattern differences in the raw data that conventional machine learning algorithms could not yet. Most sports-specific classification science, including running-related science, has historically classified movements with conventional machine learning algorithms, such as support vector machines [51, 46, 45, 152, 164, 99, 77, 47]. To classify data with conventional machine learning algorithms, scientists typically extract features from the raw data before training the classification algorithm [183]. In running, these features could for example be stride time, coefficient of variation, or minimum and maximum joint angles [207, 25, 45, 66]. Compared to conventional machine learning algorithms, modern machine learning algorithms, such as neural networks, have higher classification accuracy in biomechanics [51, 152]. Neural networks can learn from raw datasets without the need to extract features, ameliorating the risk of losing information in the data.

In this study, we used a neural network to further test whether there is information available within individual running patterns to classify individual runners' long-distance running performance. To accomplish this, 119 participants reported their personal best 10 km run time. They then ran on a treadmill at three different speeds and overground at a self-selected sub-maximal speed while we collected data from IMUs inserted in the insoles of both shoes. Using this data, we trained a neural network model to accurately identify individual runners. This confirmed that there was sufficient information in the IMU signals, and capability in our model architecture, to identify individual differences in running patterns. We then tested whether the individual differences in these running patterns could be used to separate fast runners from slow runners by retraining the same neural network to classify runner performance rather than runner identity. Failure of this model in classifying runner performance after success in classifying identity is evidence that individual running patterns do not contain useful information about a runner's capability. Our second purpose for this study was to determine how the model's accuracy in identifying individual differences in running patterns would scale with an increase in the number of runners or an increase in the amount of data for each runner.

4.3 Methods

4.3.1 Participants

We recruited 119 participants for the study (female: n = 58; male: n = 61; age: 43 ± 11 years; body mass: 69.9 ± 11.3 kg; height: 175 ± 10 cm; US shoe size: 9.2 ± 1.6; mean ± std). The Office of Research Ethics at Simon Fraser University approved the study, and we performed the methods in accordance with the relevant guidelines and regulations. All participants provided written and verbal informed consent before participating in our study. Out of the 119 participants (1 session), 37 did the same experiment again one week later (2 sessions), and 24 did the same experiment a third time (3 sessions), one month after the initial visit.

4.3.2 Experimental Design

Participants ran on a treadmill and overground and indicated their running speed. Prior to data collection, participants warmed up for 5 minutes to become familiar with the treadmill (NordicTrack C700, NordicTrack, Logan, USA). Participants then ran for 1 minute each — excluding treadmill acceleration and deceleration — at three different speeds (2.5, 3.0, and 3.5 m/s) in a randomized order. Afterwards, in a hallway, participants ran 90 meters overground in one direction, turned around, and ran the same distance in the opposite direction at their preferred speed. To quantify their running performance, participants reported their 10 km personal best time on a questionnaire.

During the experiment, we collected data with an IMU sensor mounted in both shoe insoles. An IMU (Plantiga Technologies Incorporation, Vancouver, Canada) collected both lineaer acceleration and angular velocity at a sampling rate of 500 Hz. The accelerometers' range was +/-16 g and the gyroscopes' range was +/- 2000 degrees/second. Figure 4.1 illustrates the orientation of the sensor in the insole.

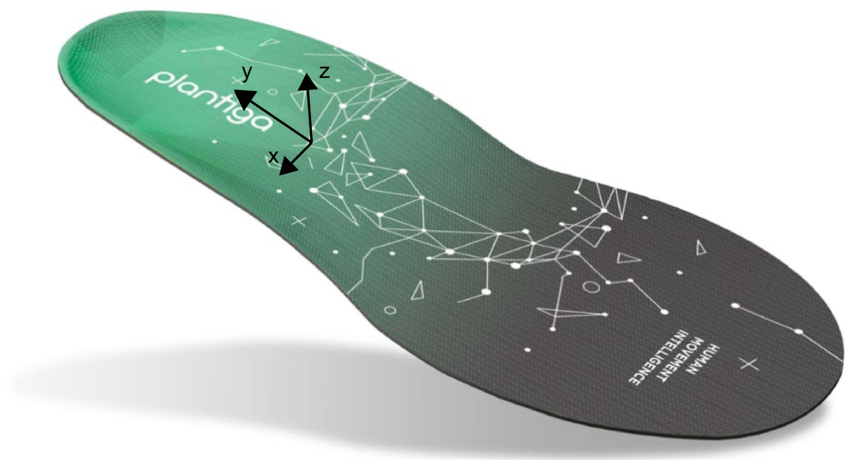

Figure 4.1: Illustrates the sensor orientation in the insole.

4.3.3 Data Preparation

We ensured steady state running in the data and then cut the data into smaller data windows. Through visual inspection, we cut the treadmill data to 50 seconds in total, to ensure steady state running in the data. Similarly in the overground running, we only included steady-state running, excluding speed changes in the beginning, during turn-around, and at the end. We split the data into data windows of 20s or 10,000 data points to capture over 95% of the variability in the data [198, 22]. To artificially increase our dataset, we used an overlap of 9,000 data points.

We then transformed linear acceleration and angular velocity data of each window into spectrograms. Figure 4.2 illustrates the transformation from a raw data window to a spectrograms. Scientists have already applied this methodology in different scientific areas, where they transformed time-series data into spectrograms and trained gold standard image recognition algorithms on these datasets [111, 237, 12]. For each window, we created one spectrogram image per sensor. To create the spectrogram, we used the spectrogram function from the signal library in Python (Python Software Foundation, Wilmington, USA), with a segment length of 250 samples (0.5s) and no overlap. Pilot tests revealed good performance with these settings. Each spectrogram consisted of 126 frequencies on the y-axis and 40 data points on the x-axis. To visualize the power of higher frequencies better, we also converted the power spectrogram into decibel units using the power_to_decibel function from the librosa library. A single input for the neural network consisted of 12 spectrogram images – one image for each sensor channel from each shoe.

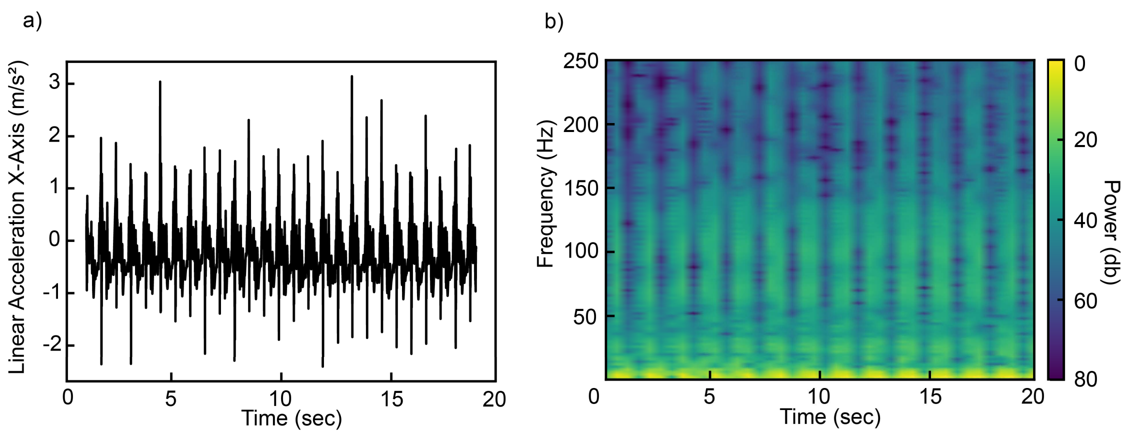

Figure 4.2: a) illustrates one representative window of linear acceleration data in the x-axis. b) illustrates the transformed spectrogram of the same data.

4.3.4 Data Analysis

We first optimized our model to predict individual runners. The model used 100% of the treadmill data for training and 80% of the overground data for validation. We left out 20% of the overground data to test the accuracy of the trained model (Figure 4.3a). The model required to use 100% of the treadmill data for training to learn the running pattern from each individual runner. For a total of 119 runners, we used treadmill data from all 119 runners for training, overground data from 95 runners for validation during training, and overground data from the left out 24 runners to test the accuracy of the trained model. During testing, the model had to predict an individual runner out of 119 possible runners. We also did some tests on the runners that did the experiment two or three times, using the same ratios between training, validation, and test set. To quantify the performance of the model during training, validation, and testing, the model calculated accuracy, which is the ratio between correctly classified runners and the sum of all runners.

As a secondary purpose, we also tested how the amount of runners and the amount of training data per runner affected the accuracy of the model. To do so, we trained the model with treadmill data from 1 session from 10 runners and used the overground data for validation. We did this test with an increasing number of runners, in increments of 10 [10, 20, 30, . . . , and 119]. We did the same test again, but reduced the amount of training data for each participant to 67%. For both tests, we used all overground data for validation, and did not reserve a separate test set.

We then optimized the model to separate fast and slow runners based on their 10 km personal best time. We used treadmill data from 60% of the runners for training, 20% for validation, and left out 20% for testing (Figure 4.3b). To prevent the model from deriving a runners' 10 km personal best time from their preferred overground speed, we excluded the overground data from this part of the analysis. For a total of 119 runners, we used treadmill data from 71 runners for training, treadmill data from 24 runners for validation during training, and treadmill data from the 24 left out runners to test the accuracy of the trained model. We trained and tested the model to predict the runners' 10 km personal best time in seconds, and quantified the model's performance during training, validation, and testing by calculating the root mean square error. Here, we also calculated the mean 10 km personal best time of all runners in the training dataset, and used this number as a prediction for every runner in the test set, and compared the result to the performance of our model's predictions. To simplify the task, we also created a fast and slow group, with the median 10 km personal best time separating both groups into equal sizes, and tested the model's classification performance in separating fast from slow runners. To quantify the model's performance during training, validation, and testing, it calculated accuracy, which is the ratio between the correctly classified group and the sum of all runners.

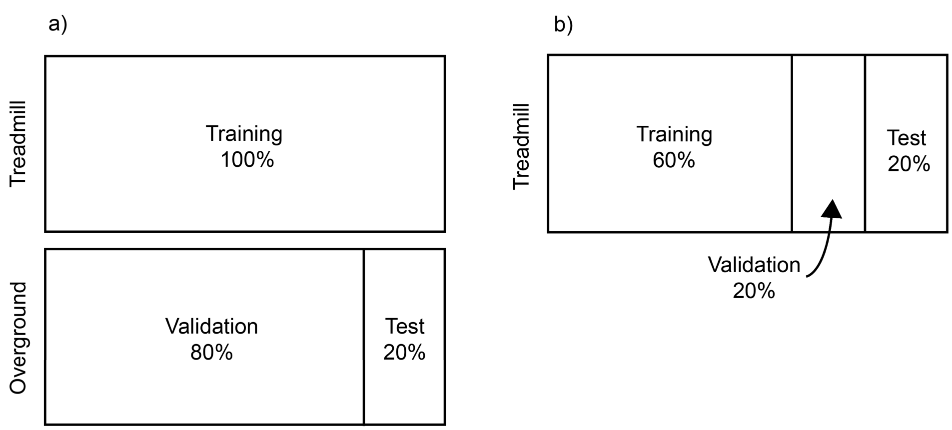

Figure 4.3: a) illustrates how we split the data in training, validation, and test set for predicting individual runners. b) illustrates how we split the data for predicting the runners' running performance.

Before training and testing the models, we chose an image recognition algorithm and optimized the hyperparameters. We used ResNet50V2 from the keras library [93], because it showed success with spectrogram classification in other scientific areas, and did all cal-

Table 4.1: Test accuracies for using 1, 2, or 3 sessions.

	1 Session	**2 Sessions**	**3 Sessions**
Total Runners	119	37	24
Test Runners	24	8	6
Test Accuracy	84%	89%	95%

culations in Google Colab (Alphabet Inc., Mountain View, USA). Based on pilot analysis, we used a batch size of 32, did 5,000 epochs, used an adam optimization algorithm with a learning rate of 10^{-5}, and automatically re-initialized the weights if the performance of the validation set did not increase for more than 1,000 epochs. Our algorithm saved the model with the best accuracy on the validation set.

4.4 Results

The model could accurately identify individual runners from their running patterns. When training and testing the model with all runners that had data from at least one experimental session, the model had a test accuracy of 84%. To arrive at this single session value, here we used the treadmill data from all 119 runners to train the model, overground data from 95 of these 119 runners for validation during training, and the remaining 24 runners' overground data for testing. It is for these test runners that the model accurately assigned the overground data to the correct runner — out of 119 possible runners — 84% of the time even though we did not train it on this data. The test accuracy increased to 89% and 95% when trained on data from 2 or 3 sessions, respectively. This increase in performance is because we had more data from each runner to train the model, and because the model had fewer runners to discriminate between. Table 4.1 presents the accuracy of these different tests.

The accuracy of the model decreased with an increased number of runners and a decreased amount of data per runner. Figure 4.4 illustrates the validation accuracies with an increasing number of participants for 100% and 67% of data per runner, respectively. When averaged over all calculations — that is with 10 runners, 20 runners, and so on —, the accuracy was on average $6.1 \pm 4.1\%$ (mean $\pm$ std) lower for the validation accuracy with 67% of the data. Here, we used all overground data for validation, and did not reserve any test data throughout the experiment.

The model could not accurately predict running performance from individual running patterns. When predicting an individual runner's 10 km personal best time, the model's root mean square error of the test set was 473 s. To arrive at this value, here we used treadmill data from 71 runners to train the model, treadmill data from 24 runners for validation during training, and treadmill data from the remaining 24 runners' treadmill data for testing. To

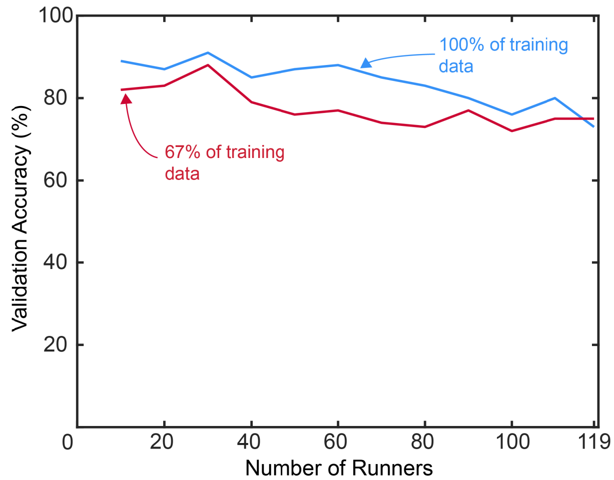

Figure 4.4: Illustrates 1) how the validation accuracy decreases, when the number of runners increases and 2) how the validation accuracy decreases when the amount of data per runner in the training data decreases.

evaluate whether the model could predict 10 km personal best times from individual running patterns, the model never saw any data from the test runners during training or validation. For comparison, we also calculated the mean 10 km personal best time of all runners in the training dataset (2759 s) and used this number as a prediction for every runner in the test dataset, which resulted in a root mean square error of 486 s. With a root mean square error of 473 s, the neural network was not much better than simply using the mean of the training runners' 10 km personal best time based on their running patterns. To simplify the task, we created a fast and slow group, with the median 10 km personal best time separating both groups into equal sizes and tested the model's classification performance in separating fast from slow runners. Here, the model was not able to accurately separate fast from slow runners based on their running patterns, with a classification accuracy of 57%.

4.5 Discussion

Running patterns are individual but do not have information about a runner's performance. To demonstrate this, participants reported their personal best 10 km run time and we collected acceleration and angular velocity data from IMUs embedded in the shoe insoles during treadmill and overground running. First, we transformed time series running data into spectrograms and trained a state-of-the-art image recognition neural network to classify individual runners from their running data. Second, we trained the same neural network to classify the runners' performance. With enough data, the neural network was successful in classifying the individual runner, but it failed to classify their performance.

The main limitations of this project are the choice of sensor and the local sample population. First, scientists collect data in running biomechanics mostly with stationary laboratory equipment such as force plates and 3D video analysis. This limits the comparison of our findings with previous findings in the area. We chose to do our study with wearable sensors, because laboratory experiments can be unrepresentative of the real world [58, 33, 17] and wearable sensors are widely seen as the future of biomechanical research [259, 208, 250, 223]. The sensor that we used can accurately measure the kinematics of the foot, and has been validated and used in other studies before [161, 212, 151, 160]. Second, because of the choice of sensor, our results only apply to foot kinematics. Our experiment does not prove that there is no information about performance in any other parts of the body. Third, because we conducted our experiment in Vancouver, our sample population is limited to runners from the Greater Vancouver Area. To mitigate this limitation as much as possible, we collected data from a comparably high number of runners.

Our experiment contradicts research that has found that there are good and bad running patterns. Clermont et al. were able to accurately classify recreational and competitive runners from their running pattern [46, 45]. Our algorithm was unable to predict the running performance from the running pattern. Clermont et al. used different data collection methods — they used an IMU at the lower back [45] and lower limb 3D video analysis [46] — and, while in our data there was no information about the running performance, the necessary information might be available in theirs. However, it is also possible that their results represent false positives for the following methodological reasons: First, in their cross-fold validation they seemed to leave out a certain amount of data, instead of leaving out a certain number of participants, which risks that an algorithm learns the association of a runner's individual running pattern with their individual running performance. Second, they included 35 and 41 runners in their studies, respectively, which is a small sample size and could also lead to a positive result by chance. Compared to that, our cross-fold validation algorithm left out all data of runners used in the test set, and our sample size was, with 119 runners, much larger. Besides our experiment, two more research groups have found no association between running patterns and performance. Agresta et al. found no association between years of running experience and trunk and lower extremity kinematics and kinetics [7]. Patoz et al. found no association between running economy and whole body kinematics [178].

An individual's running pattern generalizes to different environments. Most research in this area either trained and tested their algorithm with treadmill data or trained and tested their algorithm with overground data [97, 246]. Their prediction accuracies are >95%. Only Horst et al. switched between multiple different shoes and found that their algorithm could still predict the individual runner with an accuracy of 80% [99]. Scientists call this phenomenon domain or dataset shift, and it shows how generalizable an algorithm is to changing environments [190]. In our study, we trained the neural network on treadmill data with three fixed speeds, and tested its accuracy on overground data with the runners' preferred speed. That is, the neural network had to classify runners on a different surface and with different speeds than what it trained on. Our model was able to accurately classify runners in different running environments and adds to the findings of Horst et al. where they successfully classified runners with different footwear [99].

Individually distinguishable running patterns do not scale with increasing individuals. Some algorithms in past studies could accurately classify individual running patterns [97, 99, 246]. Weich and Vieten define this phenomenon as the "gaitprint". These three studies used between 30 and 50 runners. In our experiment, we had a bigger sample and found that, as we increased the number of runners in the analysis, the classification accuracy decreased (Figure 4.4). These results suggest that if we keep increasing the number of different runners, the accuracy of the neural network in classifying individual runners would eventually go towards 0. Decreasing the amount of data for each runner (100% vs. 67%) had a similar effect, but also suggests that by increasing the amount of data per runner, we could simultaneously increase the number of runners without losing classification accuracy. For example in our data, 10 participants with 67% of data had a similar validation accuracy as 80 participants with 100% of the data. We know that increasing the amount of data per class increases the overall accuracy of the model [196, 49, 193]. Our study added to this knowledge as it helps understand the effects of increasing the number of classes. These findings question Weich and Vieten's proposal of using the "gaitprint" as a virtual signature to mitigate fraud in e-sports such as ZWIFT (Zwift Inc., Long Beach, USA) or IRONMAN Virtual Club (Sport Heroes, Paris, France). Our results suggest that the amount of data used to create an individual's "gaitprint" will have to continuously increase as the number of participants increases.

Future research should leverage novel algorithms that can analyze image recognition algorithms to better interpret the decision making process of the neural network. Compared to most biomechanics research, which uses traditional machine learning algorithms, we used a neural network for classification. Neural networks have better capabilities in learning complex patterns in the data, but their decision making is harder to interpret [183]. Recently, different research groups have suggested algorithms that can interpret neural networks, specifically in image classification [260, 68, 258, 206]. For IMU-measured running data, these algorithms could enable us to better understand which frequencies in the linear acceleration and angular velocity data distinguish individual runners. Besides the possibility of using physics-informed neural networks [192], this could create another possibility of understanding the decision making of neural networks, and increase their importance in biomechanical analysis.

This project has significance in the areas of running biomechanics, coaching, and virtual signatures. Our algorithm could classify individual runners from their running patterns, but was not able to classify their running performance. Coaches should take this information into account when considering to adapt running patterns during training, as our findings indicate no existence of a good or bad running pattern, at least not when measuring kinematics with shoe-insole implemented IMUs. If good or bad running patterns do indeed exist, scientists should focus on measuring kinematics also from other parts of the body. Additionally, our results have significance for the consideration of running patterns as virtual signatures in e-sports. We found that running patterns generalize to different environments — in our experiment the running patterns generalized to treadmill and overground running, and different speeds —, but that the performance of the algorithm decreases with an increasing number of different individuals. In e-sports an algorithm could be able to identify an individual runner in different environments, but if the number of different runners increases without a simultaneous increase in the amount of data per runner, the algorithm's accuracy in classifying an individual runner decreases. To ensure data safety and competition fairness in e-sports, engineers will have to find a solution to confidently identify individual runners. One solution could be to continuously retrain the algorithm on the runners' new data.

Chapter 5

A remote laboratory course on experimental human physiology using wearable technology

5.1 Abstract

To help educators deliver their physiology laboratory courses remotely, we developed an inexpensive, customizable hardware kit along with freely available teaching resources. We based the course design on four principles that should allow students to conduct insightful experiments on different physiological systems. First, the experimental setup should not be constrained to laboratory environments. Second, students should be able to take this course without prior coding and electronics experience. Third, the hardware kit should be relatively inexpensive, and all other resources should be freely available. Fourth, all resources should be customizable for educators. The hardware kit consists of commercially available electronic components, with a microcontroller as its hub (Arduino friendly). All measurement systems can be assembled without soldering. The hardware kit is cost-effective (approximately the cost of a textbook) and can be customized depending upon instructional needs. All software is freely available, and we share all necessary codes in open-access online repositories for simple use and customizability. All lab manuals and additional video tutorials are also freely available online and customizable. In our particular course, we have weekly asynchronous physiology lectures and one synchronous laboratory session, where students can get help with their equipment. In this article, we only focus on the novel and open-source laboratory part of the course. The laboratory includes four units [data acquisition, ECG, electromyography (EMG), activity classification] and one final project. It is our intent that these resources will allow other educators to rapidly implement their own remote physiology laboratories or to extend our work into other pedagogical applications of wearable technology.

5.2 Introduction

Delivering effective laboratory experiences in science, technology, engineering, and mathematics (STEM) is challenging to do remotely. A goal of laboratory courses is to provide students with hands-on experience using methods and approaches relevant to the course area. In conventional laboratory courses, this hands-on experience is often enabled with the use of a small number of relatively expensive and specialized laboratory equipment in a face-to-face setting. The expensive and nonportable nature of traditional equipment make it challenging to replicate the experimental approach in a remote learning environment. That is, it has been easier to bring the students to the laboratory than the laboratory to the students. Consequently, although there is a substantial body of evidence about the effectiveness of online teaching in general [163], a commonly held view is that online teaching methods in laboratory courses are not equivalent alternatives to conventional laboratory experiences [169, 106, 243].

Compared with other disciplines in human biology, it has been especially challenging to identify appropriate remote laboratory teaching methods for physiology. In anatomy, for example, instructors can use interactive visualization to increase student engagement and learning (5, 6). In histology, virtual microscopy offers an efficient learning tool with high performance outcomes and high student satisfaction [21, 112, 30]. In physiology, the available tools are not as effective. For example, computer simulations can enhance the understanding of physiological concepts [167], but there are several reasons why not even high-fidelity patient simulators—which are lifelike computer model-driven manikins—can replace traditional teaching methods where students do physiological measurements on humans and other biological systems. These reasons include that reproducing realistic physiological scenarios can be difficult, time consuming, and expensive [94]. Recently, educators have proposed smartphone-assisted physiology laboratories, where students can learn to measure different physiological parameters such as heart rate or respiratory rate with their own smartphones [121]. Although this creative approach has many strengths, it constrains potential physiological experiments to those that are possible with phone sensors, which is a small subset of those that would normally be possible in on-campus laboratories. The lack of options for remote hands-on physiology laboratories became particularly clear to us during the COVID-19 pandemic when safety necessitated that we cancel all face-to-face classes for more than a year.

To help educators deliver hands-on physiology laboratory courses remotely, we developed an inexpensive, customizable hardware kit along with fully open-source teaching materials. Our main goals were to deliver an open-source course that teaches physiology students how to do hypothesis-driven physiological experiments and to make the course inexpensive and customizable for educators with different needs. We designed it so that students without prior coding or electronics experience would find the course material approachable.

To make the hardware kit inexpensive and customizable, it consists of commercially available electronic devices and components with a microcontroller as its hub and includes a suite of physiological sensors. With customizable laboratory manuals and supplementary video tutorials, students measure physiological signals such as electromyography (EMG), electrocardiography (ECG), and kinematics. Then, they analyze and interpret the acquired signals with open-source computer software available through source code repositories. In this article, we mainly focus on the novel part of this course, the laboratory portion. The laboratory portion includes the hardware, software, and pedagogical resources that we developed. Educators can use these resources to teach a stand-alone laboratory course and a laboratory portion for a hybrid lecture and laboratory course.

5.3 Methods

5.3.1 Course Design Principles

We had several key principles for the design of the course. First,the hardware system underlying the data collection must be wearable. That is, all sensor configurations could be worn on the body and operated without the necessity of a computer connection, using battery power and data logging capabilities. Second, extensive technical experience must not be a prerequisite for the course. Toward this principle, setting up the hard- ware should work without soldering and the number of wires and devices for a measurement system should be small. Additionally, students should not require prior coding knowledge to set up software for the measurement systems as well as the data analysis. Third, all resources must be financially accessible. The hardware kit should be relatively inexpensive (approximately the cost of a textbook), all the software required should be open source, and the instructional materials should be open access. Fourth, the workload for educators to develop a similar course must be minimal. All hardware, software, and instructional materials should be customizable. Finally, the combination of these resources must allow students to do multiple insightful experiments on a range of physiology systems. Based on these principles, we demonstrate our solutions for the hardware kit, software, and instructional materials and explain how to customize them to meet different needs.

5.3.2 Hardware Kit

The hardware kit consists of commercially available electronic components, with a microcontroller as its hub and a suite of physiological sensors (Table **??**). To make the hardware kit wearable, a 9-V battery powers the system and a data logger stores the data on a memory card, eliminating the need to be tethered to a computer. To make the system solderless, the devices connect either via jumper wires or via a specific one-wire protocol called “Qwiic” [217]. With the digital and analog input pins and the Qwiic connection, the microcontroller can connect to many state-of-the-art electronic devices without the need to solder. This allows educators to customize the hardware kit with different sensors depending upon instructional needs. The particular hardware kit that we are using (Figure 5.1) is \$130 US. In comparison, current human physiology testing kits used for conventional undergrad laboratory courses cost \$6,000 US per kit (e.g., iWorx Systems Inc., Dover, USA). This system can measure ECG and EMG at a sampling frequency of up to 1,000 Hz and three-dimensional accelerations with a range of up to ±8 g and a sampling frequency of up to 800 Hz, all at a resolution of 12 bits. When untethered from a computer, the maximum sampling frequency reduces to 50 Hz.

Table 5.1: Overview of the materials used in the hardware kit.

Component	**Cost ($US)**	**Model**	**Relevant specifications**
Microcontroller	~20	SparkFun RedBoard Qwiic	Input voltage: 7–15 V Digital and analog input pins One Qwiic connector
Analog-digital converter	~10	SparkFun Qwiic 12 Bit ADC	Operating input voltage: 2–5.5 V 12-bit resolution Programmable input gains Two Qwiic connectors
Data logger	~17	SparkFun Qwiic OpenLog	Data logging at 20 kb/s Compatible with 64 MB to 32 GB micro SD cards (FAT16 or FAT32) Two Qwiic connectors
Micro SD	~7	Any	64 MB to 32 GB FAT16 or FAT32
Accelerometer	~12	SparkFun Triple Axis Accelerometer Breakout—MMA8452Q (Qwiic)	Operating input voltage: 1.95–3.6 V Input range: ±2 g/±4 g/±8 g Sampling frequency: 1.56–800 Hz 12-bit resolution Two Qwiic connectors
EMG/ECG sensor setup	~43	Grove EMG Detector Kit	Operating input voltage: 3.3–5V Output voltage: max 3.3 V

Component	Cost ($US)	Model	Relevant specifications
12 additional electrodes	~2	Any	With Snap Connector
9-V battery holder	~3	Any	Standard 5.5 x 2.1-mm, center-positive barrel jack
9-V battery	~4	Any	
USB to micro-B cable	~5	Any	Preferably > 1m
Three Qwiic cables	~3	Any	
Ten jumper wires	~1	Any	
Carton box	~1		
Total	~128		

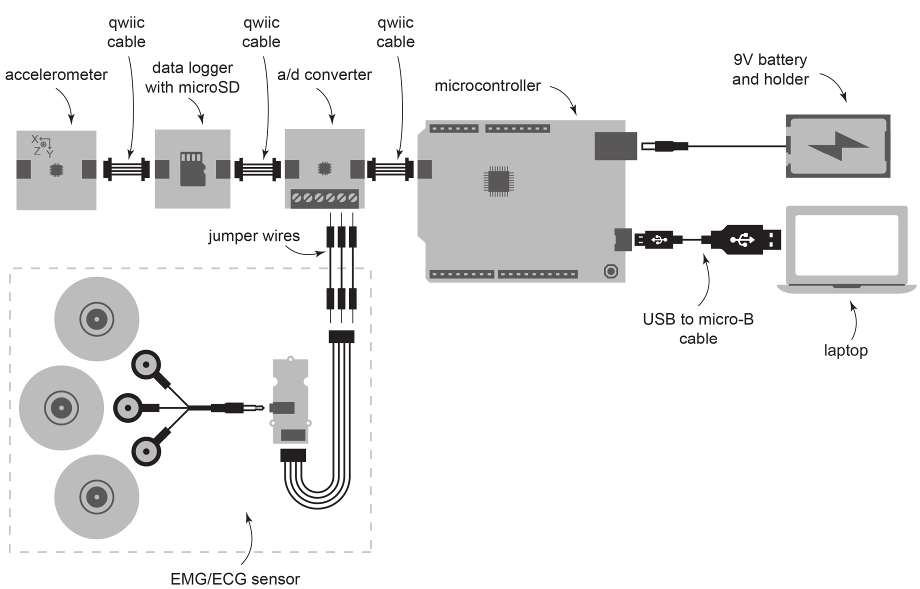

Figure 5.1: Components of the hardware kit. EMG, electromyography; ECG, electrocardiography.

5.3.3 Software and Software Repositories

We chose Arduino software to program the hardware, Python programming language for data analysis, and GitHub as the online repository. As the microcontroller is an Arduino-compatible development board, we chose Arduino IDE (Integrated Development Environment, Somerville, USA) to be the programming platform. Arduino IDE is an open-source platform that uses C and C+ programming language and is commonly used for programming microcontrollers of this type. Python (Python Software Foundation, Wilmington, USA) is an open-source programming language. As one of the most-used and fastest-growing programming languages in recent years, Python offers simple-to-use features and a great online community for support [220]. GitHub (GitHub, Inc., San Francisco, USA) is a state-of-the-art platform for source code management. Its basic services are free of charge. Programmers use it for collaborative projects and to offer their software to the general public. For each laboratory of this course, we uploaded relevant source codes and example data to a GitHub repository [132, 133, 134, 135]. We made the repositories open access for everyone, so that students can download the software, customize it if needed, and use it for their own projects. If educators want to customize the repository, they can download and edit the source codes. Educators may then add their own additional source codes and upload their collection to their own repository. Arduino IDE, Python, and GitHub are industry standards and not simplified tools for educational purposes only. Consequently, students learn how to use tools that can be applied in their subsequent careers.

5.3.4 Instructional Material

We used Google Docs for the laboratory manuals and assignments, and YouTube for supplementary video tutorials. Google Docs (Alphabet Inc., Mountain View, USA) is an open-access online word processor that allows multiple users to collaborate and edit files in real time. Additionally, Google Docs allows for document sharing with a defined group of people or web publishing to make it visible for everyone on the web. Educators can copy the laboratory manuals or assignments or the parts of them they need. They can then customize a document for their own course and share it with their students or the general public. To help students set up measurement systems and analyze data, we created a YouTube channel with supplementary video tutorials [131]. To customize this library, educators can create their own YouTube library with videos from the channel and their own additional content.

5.4 Results

Beginning in Fall 2020, we have been using these laboratory resources to teach our fourth-year physiology course remotely in the Department of Biomedical Physiology and Kinesiology. We coordinate with a local electronics store, which prepares and ships all hardware kits to our students before the semester starts (Figure 5.1). In asynchronous weekly lectures and tutorials, we teach students systems physiology concepts and how to measure and analyze physiological systems. The lecture topics include Wearable Technology, Data Acquisition, Blood Pressure, ECG, Heart Rate and Heart Rate Variability, Exercise Intensity and VO_{2max}, EMG, EEG, Activity Quantification, Pulmonary Function, and Temperature. For the laboratory component, we include five laboratory units: data acquisition, ECG, EMG, fitness tracking, and final project [140]. Students have 3 weeks to finish each unit and work in small groups of three or four members, with each group member working from their own home. To support students during their laboratories, we hold weekly 3-h-long synchronous online laboratories, where students can ask questions and teaching assistants can help with troubleshooting. For each of the four laboratories, students submit a laboratory report, and for the final project they have to submit a conference-style video presentation. This course was conducted within Simon Fraser University teaching instruction and research policies.

In the first laboratory, students use the accelerometer and the data logger to learn the principles of data collection, analog/digital conversion, data processing, and data storage (Figure 5.2) [138]. In multiple small experiments students first collect accelerometer data while being tethered to the computer to both power the system and store data. In the wearable version, they power the system with a 9-V battery while logging the data to a memory card. With the collected data, students then learn how to filter and interpret the data.

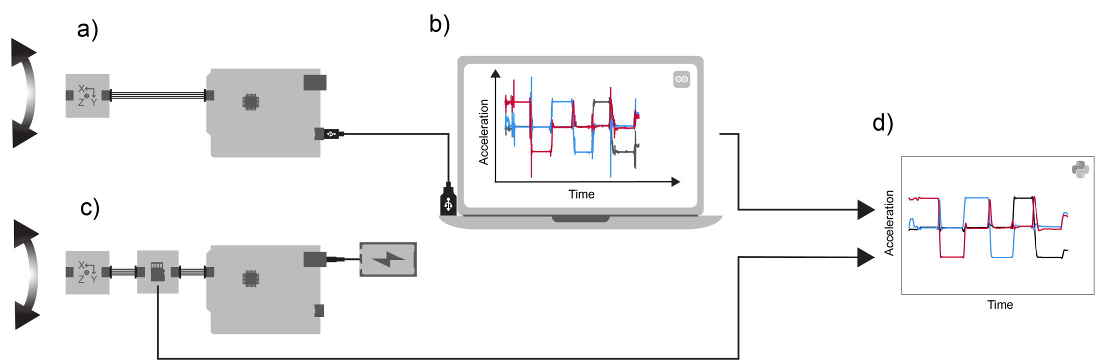

Figure 5.2: Graphical representation of the workflow for the data acquisition unit. a) the setup while being tethered to the computer. b) the wearable version with the 9-V battery and the data logger. c) 3-dimensional raw acceleration data as collected by the hardware. d) 3-dimensional, in Python, filtered acceleration data.

In the second laboratory, students set up a 1-lead ECG measurement system to collect raw ECG data and learn about heart rate, heart rate variability, and exercise intensity (Figure 5.3) [141]. Students put the two measurement electrodes on the manubrium and on the left V6 ECG placement position and the reference electrode on the C7 vertebra. In a resting experiment, students collect the data while tethered to the computer, to allow for higher sampling frequency. In an exercise experiment, students use the wearable system while doing intervals of higher and lower intensities on either a stationary or outdoor bike. For both the resting and exercise experiments, students detect the R-wave peaks with an algorithm in Python. Based on the R-wave peak intervals from the resting data they then calculate their resting heart rate and heart rate variability, and based on the R-wave peak intervals from the exercise experiment they visualize their continuous heart rate and predict energy expenditure.

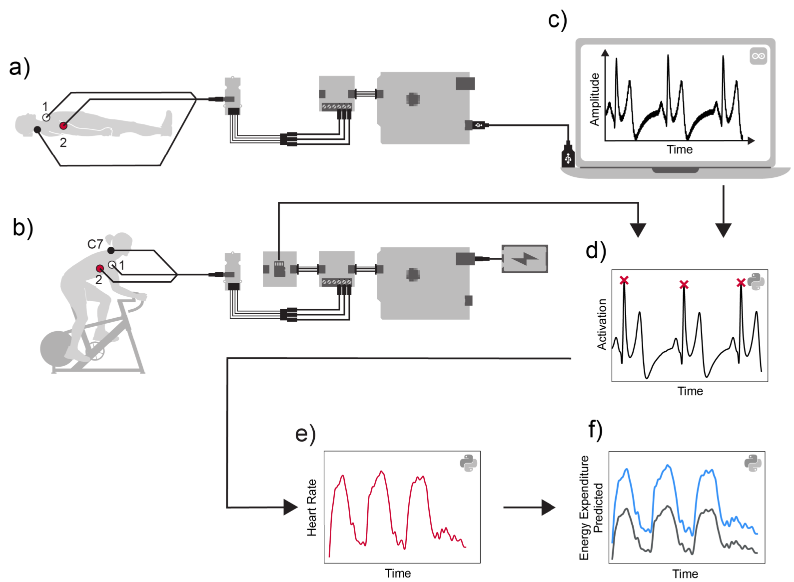

Figure 5.3: Graphical representation of the workflow for the ECG unit. a) the resting experiment setup, with the 3 electrodes, while being tethered to the computer. b) the wearable setup. c) the raw ECG data as collected by the hardware. d) the detected R-wave peaks in Python. e) continuous heart rate during the exercise experiment in Python. f) the predicted energy expenditure in Python.

In the third laboratory, students learn how to collect and filter raw EMG data and how to analyze muscle fatigue by calculating and interpreting a frequency spectrum (Figure 5.4) [142]. Students collect EMG data from the biceps muscle while holding different weights and doing maximum voluntary contractions (MVCs). In Python, students preprocess the EMG data and calculate the relative muscle activations when holding different weights. With the MVC data, students calculate muscle fatigue. They isolate three 0.5-s windows, one in the beginning, one in the middle, and one in the end of the burst, and calculate the median frequency that splits the integral of a power spectrum into two equal halves. To see how the muscle fatigues, they then compare the median frequency of the respective time windows.

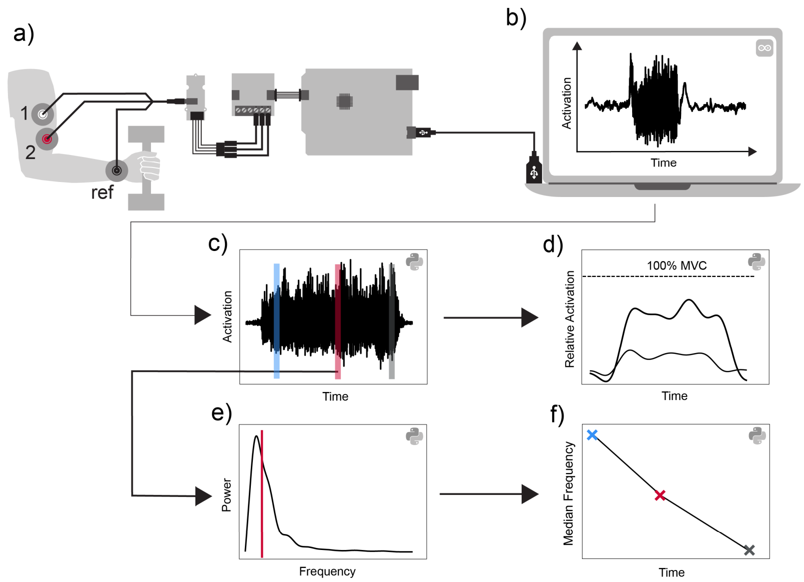

Figure 5.4: Graphical representation of the workflow for the EMG unit. a) the setup with the 2 measurement electrodes on the biceps and the reference electrode on the wrist. b) raw EMG data of a single burst as collected by the hardware. c) the preprocessed EMG data and the 3 isolated windows at the beginning, middle, and end of the burst in Python. d) the relative muscle activations when holding different weights in Python. e) the median frequency that splits the integral of a power spectrum into 2 equal halves in Python. f) the change in median frequency of the respective time windows in Python. MVC, maximum voluntary contraction.

In the fourth laboratory, students learn how to build a wearable, battery-powered fitness tracker that measures wrist accelerations, automatically classifies different activities, and counts steps (Figure 5.5) [139]. With a self-built wearable accelerometer on their wrist, students collect acceleration data during lying, standing, walking, and running. In Python they then label their own data. Every student uploads their labeled data to a shared folder. Each group trains a neural network model for activity classification with the data of the other groups and tests the accuracy of the activity classification model on their own group's data. Additionally, students develop a simple step-counting algorithm by high-pass filtering the acceleration data and finding the peaks.

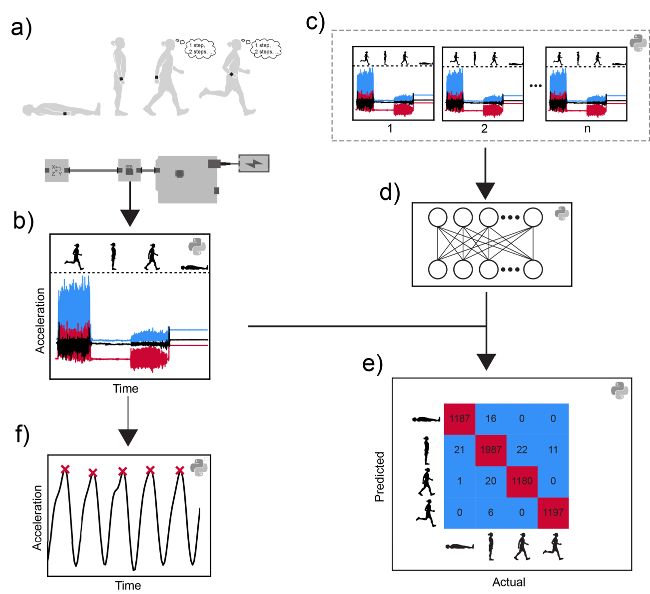

Figure 5.5: Graphical representation of the workflow for the activity classification unit. a) the wearable setup of the fitness tracker. b) 3-dimensional raw acceleration data during running, standing, walking, and lying in Python. c) and d) students use the collected data sets of their classmates (c) to train their own neural network in Python (d). e) the confusion matrix result when testing the trained neural network's accuracy with the student's own data from B in Python. f) the low-pass filtered acceleration data with the found peaks at each step of their walk or run in Python.

In the final project, students identify an interesting physiological question. They generate hypotheses, develop and perform their own experiments, and analyze and interpret the data to test their hypotheses and answer the original question. For example, one group in the first semester compared the heart rate and heart rate variability between rest and watching a scary video. Another one compared the EMG of doing squats with differently positioned feet. We also allowed for more technological projects. One group, for example, tried to evaluate the accuracy of a self-built accelerometer-based device that measures jump height.

For the experiment, each group member would collect the data on themselves. They could then analyze data of three or four people and interpret the results accordingly.

To assess the students, we use a combination of online quizzes, assignments, and writings. Before each weekly synchronous online laboratory session, students have to do a 10-min-long quiz with 5–12 questions. We include questions about the physiological systems and about the laboratory tasks to evaluate students' knowledge from the physiology lectures as well as from the laboratory parts, respectively. For each of the four laboratory units, students have to submit an assignment, in which they have to answer questions about the laboratory tasks, and submit their own collected and analyzed data sets. For the final project, students submit a formal proposal of their project about halfway through the semester. Toward the end of the semester, they then submit a journal-style paper and a conference-style presentation. We review the proposal and help them revise it to be both feasible and useful. We assess the journal-style paper based on an extensive marking rubric. Students have to demonstrate their background knowledge of the topic, the relevance of their project, a clear description of the methods, insightful results, and a thoughtful discussion. For the presentation, we also assess their clarity and presentation skills. We do not assess the students' knowledge through exams.

To assess the students' perception of the course, we use standard university student evaluation forms at the end of the semester and weekly anonymous feedback forms throughout the semester. Our perception after three semesters is that students find the course challenging but valuable. As expected, most students do not have prior experience with electronics and coding. Our general impression — based on student evaluations at the end of the semesters as well as speaking with students throughout the semester — is that most students find the practical component difficult but worthwhile and perceive the workload as being high. For example, one student reported: "My only complaint about this course was the time commitment. Overall, the hands-on aspect helped me learn more effectively than any other course I've taken." Another student reported: "This was one of the most challenging BPK [Department of Biomedical Physiology and Kinesiology] courses I've had to take in my undergraduate studies. In the end, I can genuinely say that I enjoyed the course even if I wasn't the best at using Python." Students perceived the videos to be crucial for their success. For example, one student reported: "The course was very well done considering the conditions. Bugs were frequent and frustrating working with the electronics and coding, but the videos were lifesaving." Overall, our impression was that despite the major time commitment and the many difficulties associated with a first-time course offering, students valued this new and innovative approach to hands-on, remote, and experiential learning about physiological systems and how to study them.

Quantitative evaluations in the student evaluation forms were positive. In total, 107 students took and evaluated this course in the first three consecutive semesters of offering the course. Students had to score four statements between 1 and 5, with 1 being complete disagreement and 5 being complete agreement with the statement. The first statement was "The different course activities/components (lectures, discussions, assignments, etc.) were connected" and scored on average 4.12 (SD 0.9). The second statement was "Course activities/components (lectures, discussions, assignments, etc.) helped me learn" and scored on average 4.27 (SD 0.88). The third statement was "Course materials (textbooks, library articles, and website links) improved my understanding of the course content" and scored on average 4.13 (SD 0.99). The fourth statement was "The assessments in this course (tests, assignments, essays, etc.) allowed me to demonstrate my understanding of the course content" and scored on average 4.11 (SD 0.79).

5.5 Discussion

Although this approach to remote learning has many positive attributes, it also has several limitations. First, the performance of the measurement systems is limited. Particularly for EMG and ECG measurements, expensive laboratory equipment will provide more accurate and reliable data. Second, this course requires a specialized skill set from its teaching assistants. To support students, teaching assistants not only need to understand the underlying physiology but also need to understand the hardware and software used in this course. We solved this problem with two mechanisms: New teaching assistants got an introduction to the resources before the semester starts, and former, experienced teaching assistants were available for any additional help if the current teaching assistants needed guidance. Third, troubleshooting is challenging and time intensive. Teaching assistants have to help students troubleshoot hardware and software problems via online meetings, which is not as effective as in-person support, and sometimes not sufficient. To ameliorate this limitation, we always provided example data via the GitHub repositories in order for students to continue their analysis even if they could not finish data collection. And finally, students without prior coding experience appeared to have a significantly harder time in finishing the programming parts of the laboratories compared with more experienced students. An effective, but incomplete, solution was for students to watch several Python and Arduino introduction tutorials before the start of the first laboratory.

We envision that this course will complement rather than replace conventional, hands-on laboratory courses. Conventional, on-campus laboratory courses currently have two main advantages. First, laboratory systems generally provide better measurement accuracy and reliability compared with wearables [252]. It is important for students to learn how to use these gold-standard measurement systems, specifically for those who want to follow a career in experimental physiology. And second, teaching laboratory courses on campus allows educators to more efficiently support students during the laboratory sessions, like, for example, when helping students during troubleshooting.

Compared with conventional laboratory courses, this approach offers several new opportunities. In conventional laboratories students typically work in groups, because there is a limited number of measurement devices. In this remote version, every student has their own laboratory kit, allowing each student to use the equipment and learn to collect data. This increases the overall data collected during a laboratory unit and provides the opportunity to do large studies by class-sourcing data (e.g., activity recognition experiment in unit 4). The customizability of the resources can help educators to use this laboratory kit in several different courses in multiple departments. Whereas we used it to teach how to do physiological experiments, it may instead be used in a hands-on engineering course. This opens the possibility of interdisciplinary courses in which students from different disciplines learn together. The customizability also enables students to innovate on the provided resources to design and test their own ideas. For example, students from physiology, engineering, and business could collaborate in an entrepreneurship course, where they develop a business to go along with the research and development of their wearable sensor product.

5.6 Commentary

To compare quantitative evaluations of this course, I also gathered standard university student evaluation form answers from a comparable laboratory course. The comparable course was BPK 407 - Human Physiology Laboratory, an in-person laboratory course. The numbers presented here are averages from the spring and fall semester of 2019 — the course was not offered in the summer semester —, which was the last time this course was finished before the onset of the Covid-19 pandemic. In total, 75 students filled out the standard university student evaluation forms. The first statement was “The different course activities/components (lectures, discussions, assignments, etc.) were connected” and scored on average 4.82 (SD 0.43). The second statement was “Course activities/components (lectures, discussions, assignments, etc.) helped me learn” and scored on average 4.71 (SD 0.48). The third statement was “Course materials (textbooks, library articles, and website links) improved my understanding of the course content” and scored on average 4.59 (SD 0.61). The fourth statement was “The assessments in this course (tests, assignments, essays, etc.) allowed me to demonstrate my understanding of the course content” and scored on average 4.84 (SD 0.35).

Chapter 6

Discussion

The main purpose of this thesis was to develop and test tools that can simplify the process of gathering objective data during sports, analyzing these data, and providing automatic real-time feedback to the athlete and the coach. In four different projects, I developed wearable measurement technologies, data analysis systems and models, and control systems, and provided novel insights to the running, cycling, and education literature.

In **Chapter 2**, I demonstrated how a simple and generalizable approach to develop a feedback control system could accurately and responsively control power output in cycling [143]. I developed and experimentally tested a physics-based model that could accurately predict the cycling power output with the cadence and the gear ratio as an input. I used this model in a simulation of a feedback control system and optimized for the proportional and integral gains of the feedback controller. I then implemented this controller in outdoor cycling and — for a single pilot participant — showed how it could accurately and responsively control the cyclist's power output by commanding the cadence in real-time. By first developing a model of the system dynamics, scientists can simplify the optimization of the feedback controller modifications through simulations, and replace a trial and error approach that could potentially cost lots of time [15].

In **Chapter 3**, I demonstrated how a data-driven approach could simplify the development of models by comparing a physics-based and a neural network model in predicting cycling power [136]. I developed a physics-based and a simple neural network model and compared the performance of each model experimentally in predicting outdoor cycling power with changing cadence and gear ratio as inputs. The neural network model was able to predict power with similar performance as the physics-based model. The advantages of the neural network model was that it did not require an understanding of the underlying principles of cycling nor did it require measurements of fixed parameters such as system weight or wheel size.

In **Chapter 4**, I demonstrated how a neural network accurately classified individual runners but not running performance. I measured linear acceleration and angular velocity from sensor-implemented insoles while runners ran on treadmill and on overground. I transformed the data into spectrogram images, trained an existing image recognition algorithm, ResNet50V2 [93], on treadmill data, and tested how well it could classify individual runners with overground running data. Depending on the amount of data available during training, the algorithm could accurately classify individual runners. Only using treadmill data to normalize for speed, I then tested whether the same algorithm could classify a runner's long-distance running performance, based on their personal best 10 km run time. Here, the algorithm failed to do so.

In **Chapter 5**, I demonstrated how we could effectively teach important human data collection and analysis concepts with wearable technology, remotely. I developed an affordable hardware and software kit, and all educational materials to teach an upper-level university course. After teaching the course and analyzing the students' feedback, I found that it was possible to successfully teach students how to build wearable sensor prototypes, and how to measure and analyze human data. Additionally, our resources provide educators from different institutions with the opportunity to implement similar courses for both teaching in-person and remotely. They can use the course as is, but also edit it to their own needs [137].

6.1 Thesis-overarching Limitations

The sample population was not perfectly representative. A main goal of doing human experiments is to have a diverse and representative sample. That is, scientific studies should include diverse populations such as different ages, races, sexes, and genetics, which can be very challenging in locally done laboratory experiments. In this thesis, all four projects were based on a very local sample of participants. Specifically in Chapter 2, I only used one individual. The goal here was to present a proof-of-concept of the methodology for developing a feedback control system in sports. I succeeded with one individual, but further experiments will have to test and verify the results. The 9 cyclists in Chapter 3 were mainly young and healthy individuals from the Greater Vancouver Area. Here, the goal was to optimize the models for each individual cyclist and not for the general population. Therefore, our priority was to have a diverse dataset (i.e., different cadences and gear ratios) for each individual cyclist, rather than having a high number of cyclist. In Chapter 4, our sample population was also exclusively from the Greater Vancouver Area, but we tried to minimize unrepresentative results by having a greater sample size than typical biomechanics experiments. In Chapter 5, the results are from teaching the course through Simon Fraser University, and therefore the sample is also restricted to mainly young students from the Greater Vancouver

Area. Other universities should test this approach to get a better understanding of how it applies to other populations.

Even though this thesis is based on the idea of an artificial sport coach, I did not choose a single overarching sport for this thesis. Chapter 2 and 3 laid the foundation for an artificial sport coach in cycling as it can help cyclists accurately enforce a pre-determined power profile within a single training session. Instead of continuing with cycling projects, I chose different areas for the following reasons: For Chapter 4, I identified an important knowledge gap in the running literature while continuing to further explore interesting research methods. And for Chapter 5, when the COVID-19 pandemic shut down all in-person teaching, there was an opportunity to fill a much needed gap in the remote education literature — teaching hands-on laboratory skills — , which simultaneously enabled 100s of students to proceed with their university program.

Because I focused on different areas of research in every chapter of this work, my thesis is very broad and therefore sometimes lacks depth in the individual projects. Each chapter's aim was to investigate a knowledge gap in a different area, taking away from the depth a more traditional thesis could have had. For a more traditional approach, I could have chosen one chapter of the thesis, and expanded it into its individual thesis with multiple projects. To illustrate, how an individual thesis for each chapter could have looked like, I will go over each chapter, and propose multiple projects to add depth:

6.1.1 Chapter 2:

In Chapter 2, all projects would lead towards one main goal: To answer whether an auditory feedback control system, where we control the mechanical power by commanding cadence, can improve the pacing performance in cycling. Having optimal pacing strategies can be important for cycling performance [40, 251], and aggregated pacing information (i.e., real-time feedback on a display) can lead to better pacing than with non-aggregated pacing information (i.e., written information with pacing plan and measured power on a display) [65]. Additionally, there is very limited knowledge on how much variability cyclists have during pacing [130]. Therefore, in Project 1, we would test how well cyclists can pace their power with and without aggregated information about the actual and target power displayed on a monitor. In Project 2, we would develop our prototype for a feedback control system in cycling, such as we did in Chapter 2 of this thesis [137]. In Project 3, we would optimize the physics-based model, like we did in 2.3.1, with the same participants as in Project 1. In Project 4, we would then use simulations to optimize for the best feedback controller modifications, and then test the cyclists' pacing performance with our feedback control system in outdoor cycling, similar to 2.3.2 and 2.3.3 and with all participants from Project 1 and Project 3. We could then compare these results to the pacing performance in Project 1.

6.1.2 Chapter 3:

In Chapter 3, the main goal would be to understand how simple physics-based models and complex physics-based models compare with neural network models and physics-informed neural network models. Additional goals would be to better understand how the amount of data impacts the results, and how we can best choose the best neural network model for individual projects. Some non-biomechanical experiments have already directly compared physics-based models with neural network models [42, 102]. In biomechanics, many scientists use physics-based models for example to better understand how humans walk [10] or how muscles work [38]. Others use neural networks, for example to process and predict kinetic and kinematic data [156]. Yet, there is not much knowledge on how different physics-based models compare directly to neural-network equivalents. Only one experiment has recently compared the outcomes of a physics-based neuromusculoskeletal model with a neural network model [257] in estimating joint torques. As well, it is still unclear how to best find a good architecture and hyperparameters for a neural network model [51]. Therefore, Project 1 would compare a simple physics-based model with a neural network in predicting cycling power, just like we did in Chapter 3 [136]. We would also try to understand how the amount of data as well as different architectures and hyperparameters affect the neural network model's performance. Project 2 would then add more variables to the models, such as measured drag, or wheel resistance [128], to compare a neural network with a more complex physics-based model, when there are more input variables to the models. In Project 3, we would then test whether a physics-informed neural network model could improve the neural network models from Project 1 and 2. In physics-informed neural network models, physical laws incorporated into the neural network can restrict the range of possible solutions, and therefore decrease the amount of time and data required to train the model [192]. And in Project 4, we would bring it all together in a different area and compare the prediction performances of a state-of-the-art neuromusculoskeletal model, a neural network model, and a physics-informed neural network model.

6.1.3 Chapter 4:

In Chapter 4, our goal would be to better understand what defines individual running patterns and how running patterns affect running performance. Additional goals would be to understand how the amount of data and the number of runners effects the performance of the model. Here, we would collect all running pattern data in the beginning, and we would do measurements with industry standard laboratory equipment (i.e., 3D motion analysis and force plate) and industry standard wearable technology (i.e., IMUs at different locations). In Project 1, we would test the method of using Resnet-50 in combination with spectrograms — which is a method that has been successfully used in other areas of research [41, 201] — with the 3D video data and force plate data, and also test how the amount of data and the number of runners affects the prediction performance. This would add some important information to research that was able to predict individual runners, but failed in clarifying how well their models scaled [97, 99]. In Project 2, we would do the same data analysis, but with the IMU data from different locations [246]. This would also give us an opportunity to compare the in-the-field IMU analysis with the laboratory analysis from Project 1. In Project 3, we would try to better understand which parts of the running pattern defines individual running patterns. We would use algorithms such as grad-CAM [206], that can highlight the parts in the spectrogram with the most influence on the decision making process of the neural network, which could then allow us to better understand which data channels, as well as which frequencies define individual running styles. In Project 4, we would then combine all of the gained knowledge from the first three projects, and try to predict running performance based on the different data channels that measured the running pattern. We would also compare our analysis methods with methods from scientists that claim success in predicting running performance with 3D video data [46] as well as with IMUs [45]. If we were successful in predicting performance, we would also use algorithms such as grad-CAM to analyze which parts in the running pattern were most important to predict running performance.

6.1.4 Chapter 5:

In Chapter 5, the goal would be to better understand how laboratory courses taught online compare to laboratory courses taught in-person. There is much evidence that teaching remotely can be as effective, and often even more effective, than teaching in-person [163, 145]. Unfortunately, teaching laboratory classes remotely has been more challenging to implement in the past [243]. We pursued this project because of the effects that the Covid-19 pandemic had on universities. I will only go into two specific projects that seemed to fill obvious gaps in the literature. In Project 1, we would develop and teach the course, to test whether it is possible to develop such a remote laboratory course, and whether students in general can learn important hands-on laboratory skills using such a method [137]. In Project 2, we would then use these resources to teach the exact same course, but with two groups, a remote and an in-person group. This would enable us to directly compare the learning outcomes.

6.2 Next Steps

For Chapter 2, the next steps involve fine-tuning and validating the cycling system, and developing and testing similar control systems in other areas of sports. To fine-tune our cycling system, we would have to collect data of a higher number of cyclists. Then, we would compare our feedback control system's pacing performance with other common ways of pacing, such as a monitor that displays target and measured power. Similarly, we should test how well this approach of developing a feedback control system works in different sports. For example, in swimming stroke by stroke feedback could potentially help athletes control their pace in different training sessions, such as interval training.

For Chapter 3, the next steps involve leveraging the model for a bigger population and comparing data-driven models with physics-based models in other sports. Currently, our cycling model works for a range of cadences and gear ratios. We optimized and tested our models in two experiments. First, we trained and tested the models' prediction performance within each trial, where the gear ratio did not change. Second, we trained and tested the models' prediction performance within each participant, where the gear ratio did change. In a next step, we would test how well the models work when the participants also change during training and testing of the model. To do so, the model would require information about the individual participant that can affect the power during cycling, such as weight and height [128]. We would train the model with the data of a certain number of cyclists while leaving out the data of others for validation and testing. To test the general applicability of data-driven models, we would do similar projects, where we compared data-driven models with physics-based models in other sports, such as in swimming [211, 159].

For Chapter 4, next steps involve further investigation of the relationship between the running pattern and the running performance as well as the application of our methods in other biomechanical research. To better understand if there was a good and a bad running pattern, we should analyze additional data from additional body parts, similarly to the data collected by Clermont et al., where they were able to distinguish between recreational and competitive runners from their running pattern [46, 45]. Another next step could be to use algorithms such as Grad-CAM [206] to interpret the decision making of the image recognition algorithm, for both predicting individuals and their performance. This would help understand which movements as well as which frequencies in the movements measured from the sensor define an individual running pattern and the runner's performance.

For Chapter 5, next steps involve creating a better understanding for how teaching laboratory skills remotely compares to in-person teaching, and testing our approach in different departments and universities. Our findings showed that students could learn important hands-on laboratory skills with our resources. Yet, it is still unclear how the remote approach directly compares to an in-person approach. Our resources allow for a follow-up experiment that directly compares the learning outcomes of teaching laboratory skills with wearable sensors remotely and in-person with the same resources. This could create novel and important insights in the remote education literature. Similarly, our course should be tested for its usefulness in different departments and universities with a more diverse sample population. Some universities have already adapted our resources for their own teaching (e.g., Queens University [1]). We could analyze the learning performance results of these courses in different departments and universities.

6.3 General Implications

Developing real-time feedback control systems in sports can help athletes accurately enforce their training programs to improve performance and decrease injury risk. In Chapter 2 I developed a feedback control system that accurately controlled the movements of an athlete within a training session, using the example of controlling power during cycling through auditory feedback. This system could help athletes to accurately enforce different training programs, such as interval training. This approach can help scientists and engineers develop similar systems for other sport applications. A few examples of similar control systems in sports already exist. Snaterse developed a system that controls running speed by commanding step frequency with the rhythm of music [214]. Van Berghe et al. use the rhythm of music to control step frequency to reduce tibial shock and potentially reduce injury risk [240].

Data-driven models can simplify the development of models when we do not need to understand the underlying principles of the modeled mechanism. Accurate models are important to predict training outcomes [229], and can be useful to develop control systems as I showed in Chapter 2. Using the strength of mathematical models in science and engineering can be challenging, especially when the underlying mechanisms of the natural phenomenon to be modeled are complex or unknown. In Chapter 3 I demonstrated how a data-driven approach could replace a physics-based approach in modeling the cycling power. Most scientists who are able to use data analysis software such as Python (Python Software Foundation, Wilmington, USA) or Matlab (The MathWorks, Inc., Natick, USA) can develop data-driven models. For example, to model the dynamics of cycling in Chapter 3, a simple neural network with one hidden layer was able to predict the power as accurately as a physics-based model. In Python, a single line of code built this model, which could then automatically learn from measured data. Therefore, using a data-driven approach could help develop models in different areas of sports biomechanics more easily. In other areas of engineering, such as in predicting different metrics in motorized vehicles, scientists also support the advantages of data-driven models when compared to physics-based models [42, 102].

Results in Chapter 4 contradict science stating that there are differences in running patterns between different running performances. Clermont et al. were able to accurately classify recreational and competitive runners [46, 45]. In contrast, my algorithm was not able to distinguish between fast and slow runners. The difference might be because 1) our data from the shoe-insole implemented sensor did not have the required information, 2) I used a different cross-validation method that minimizes the chance for a false positive result, and 3) Clermont et al. had a small sample size in both experiments increasing the chance for positive results by chance. Additionally, Agresta et al. and Patoz et al. support our findings [7, 178]. They did not find an association between increased years of running experience or running economy and 3D motion analysis metrics.

Individual running patterns, measured with IMUs in the insoles of the running shoes, generalize to different environments but do not scale with increasing individuals. Previous experiments trained and tested their algorithm with treadmill data or trained and tested their algorithm with overground data [97, 246, 99]. In Chapter 4, my algorithm could accurately classify individual runners with data from preferred-speed overground running, after being trained with data from three predetermined speeds on the treadmill. This demonstrates that running patterns are individual and generalize to different environments. Yet, I also found that by increasing the number of runners in the analysis, the classification accuracy decreased, challenging science that claims that e-sports companies could use the individual running pattern for virtual signatures [246].

Educators can use wearable technology to effectively teach students how to develop and use human measurement systems, even when in-person teaching is not possible. In Chapter 5 I demonstrated that there are two separate opportunities with wearable technology in education. First, wearable technology can create a learning opportunity for many people that might otherwise not be able to learn laboratory skills because of the inability to participate in in-person classes, whether that is because of their personal or external circumstances. For example, at Simon Fraser University, this course enabled 100s of students to continue their course work, and learn important hands-on laboratory skills, during the COVID-19 pandemic. Second, students learn how to use wearable technology to measure important health and sports-related factors in more realistic environments, outside of the laboratory.

6.4 Concluding Remarks

I am hoping that this work will enable growing or established scientists and engineers to build their own automatic biofeedback systems in various areas. As different smart tools, such as smartphones, large language models (LLMs), and self-driving cars, use data-driven models and feedback control systems to increasingly improve our everyday lives, we should also advance these technologies in the sports and health areas. Even though I have chosen the area of sports, feedback control systems can also help control humans in many other areas, such as health and rehabilitation. For example in health, feedback systems, such as artificial pancreas [91], will be able to accurately deliver insulin automatically and continuously. Similarly in rehabilitation, feedback systems can automate patients' home exercises [31]. With the tools in this thesis, scientists and engineers will be able to develop prototypes to measure various human variables with wearable technology (Chapter 5), analyze these data and develop models with data-driven algorithms (Chapter 3 and 4), and use models in simulations to develop accurate and responsive biofeedback systems (Chapter 2).

Hopefully you enjoyed reading through this thesis as much as I did working on the projects.

Patrick

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Appendix A

Additional Equations for Chapter 2

We modeled the system as forces acting on a point-mass m. We assumed the sum of the forces to be the horizontal forward force of cyclist with the bike $F_{cyclist}$ and some counteracting air resistance force F_{drag}. By using Newton's second law, with $\dot{v}$ being the rate of change of the cyclist's speed, we formulated the following equation to describe the cyclist's motion:

$$F_{inertial} = -m\dot{v} = F_{cyclist} - F_{drag} \tag{A.1}$$

F_{drag} is dependent on the squared speed (v^2), the air density (ρ), the frontal area of the cyclist (A), and the drag coefficient (C_d) [26]:

$$F_{drag} = \frac{1}{2} A C_d \rho v^2 \tag{A.2}$$

Due to multiple reasons, we replaced all but the squared velocity with one single variable which we call the drag number (c). First, we did not measure frontal area or air density. Second, our drag number is not only air drag but subsumes all other factors of drag, such as rolling resistance. Isolating $F_{cyclist}$ in equation A.1, and substituting the product of the squared speed and the drag number for F_{drag}, yields:

$$F_{cyclist} = m\dot{v} + cv^2 \tag{A.3}$$

We then replaced $F_{cyclist}$ with the fraction of the pedal torque τ_p and the pedal crank arm length l_p:

$$\frac{\tau_p}{l_p} = m\dot{v} + cv^2 \tag{A.4}$$

Multiplying both sides with l_p and the pedal crank arm's angular velocity ω_p yields:

$$P_{cyclist} = \omega_p l_p m\dot{v} + \omega_p l_p cv^2 \tag{A.5}$$

,where $P_{cyclist}$ is the mechanical power that the cyclist is applying to the pedal. We replace ω_p with the fraction of the linear pedal speed v_p and l_p, yielding

$$P_{cyclist} = v_p m\dot{v} + v_p c v^2 \tag{A.6}$$

We can replace v_p with the product of v, the gear ratio GR, and the fraction of the rear wheel radius r_{rw} and l_p, yielding:

$$P_{cyclist} = \frac{r_{rw}}{l_p} \cdot GR \cdot m \cdot \dot{v} \cdot v + c \cdot \frac{r_{rw}}{l_p} \cdot GR \cdot v^3 \tag{A.7}$$

We calculated speed as a function of cadence, f, measured in revolutions per minute:

$$v(t) = \frac{1}{60} 2\pi \cdot r \cdot GR \cdot f(t) \tag{A.8}$$

We took the derivative of v with respect to time t to get $\dot{v}$ and by substituting for v and $\dot{v}$ into equation A.7, we determined the power as a function of cadence:

$$P_{cyclist}(t) = \frac{4\pi^2 m \cdot GR^3 \cdot r^3}{60^2 \cdot l} \cdot \dot{f}(t) \cdot f(t) + c \cdot \frac{8\pi^3 \cdot GR^4 \cdot r^4}{60^3 \cdot l} \cdot f^3(t) \tag{A.9}$$

We then defined the time delay t_d between the commanded and the actual cadence, to get an equation that describes $P_{cyclist}$ as a function of commanded cadence $f(t - t_d)$:

$$P_{cyclist}(t) = \frac{4\pi^2 m \cdot GR^3 \cdot r_{rw}^3}{60^2 \cdot l_{rw}} \cdot \dot{f}(t - t_d) \cdot f(t - t_d) + c \cdot \frac{8\pi^3 \cdot GR^4 \cdot r_{rw}^4}{60^3 \cdot l_p} \cdot f^3(t - t_d) \tag{A.10}$$

Appendix B

Supplementary Data

B.1 SFU BPK Wearables - Lab Overview

Description:

The accompanying PDF file shows the course overview for the course developed in Chapter 5.

Filename:

SFU BPK Wearables - Lab Overview.pdf

B.2 Lab Manual 1 - DAQ

Description:

The accompanying PDF file shows the lab manual of lab 1 for the course developed in Chapter 5.

Filename:

Lab Manual 1 - DAQ.pdf

B.3 Lab Manual 2 - ECG

Description:

The accompanying PDF file shows the lab manual of lab 2 for the course developed in Chapter 5.

Filename:

Lab Manual 2 - ECG.pdf

B.4 Lab Manual 3 - EMG

Description:

The accompanying PDF file shows the lab manual of lab 3 for the course developed in Chapter 5.

Filename:

Lab Manual 3 - EMG.pdf

B.5 Lab Manual 4 - Activity Classification

Description:

The accompanying PDF file shows the lab manual of lab 4 for the course developed in Chapter 5.

Filename:

Lab Manual 4 - Activity Classification.pdf

B.6 Lab1Code1

Description:

The accompanying .ino file shows the first microcontroller code required for data collection in lab 1, developed in Chapter 5.

Filename:

Lab1Code1.ino

B.7 Lab1Code2

Description:

The accompanying .ino file shows the second microcontroller code required for data collection in lab 1, developed in Chapter 5.

Filename:

Lab1Code2.ino

B.8 Lab1Code3

Description:

The accompanying .ino file shows the third microcontroller code required for data collection in lab 1, developed in Chapter 5.

Filename:

Lab1Code3.ino

B.9 Lab1Code4

Description:

The accompanying .ino file shows the fourth microcontroller code required for data collection in lab 1, developed in Chapter 5.

Filename:

Lab1Code4.ino

B.10 Lab2Code1

Description:

The accompanying .ino file shows the first microcontroller code required for data collection in lab 2, developed in Chapter 5.

Filename:

Lab2Code1.ino

B.11 Lab2Code2

Description:

The accompanying .ino file shows the second microcontroller code required for data collection in lab 2, developed in Chapter 5.

Filename:

Lab2Code2.ino

B.12 Lab3Code1

Description:

The accompanying .ino file shows the first microcontroller code required for data collection in lab 3, developed in Chapter 5.

Filename:

Lab3Code1.ino

B.13 Lab4Code1

Description:

The accompanying .ino file shows the first microcontroller code required for data collection in lab 4, developed in Chapter 5.

Filename:

Lab4Code1.ino

B.14 Lab2Functions

Description:

The accompanying .py file includes all python functions required for the data analysis in lab 2, developed in Chapter 5.

Filename:

Lab2Functions.py

B.15 Lab3Functions

Description:

The accompanying .py file includes all python functions required for the data analysis in lab 3, developed in Chapter 5.

Filename:

Lab3Functions.py

B.16 Lab4Functions

Description:

The accompanying .py file includes all python functions required for the data analysis in lab 4, developed in Chapter 5.

Filename:

Lab4Functions.py