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Design and validation of an improved wearable foot-ankle motion capture device using soft robotic sensors

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Design and validation of an improved wearable foot-ankle motion capture device using soft robotic sensors

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A Thesis
Submitted to the Faculty of Mississippi State University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical and Computer Engineering in the Department of Electrical and Computer Engineering

Mississippi State, Mississippi

April 2021
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2021
Soft robotic sensors (SRSs) are a class of pliable, passive sensors which vary by some electrical characteristic in response to changes in geometry. The properties of SRSs make them excellent candidates for use in wearable motion analysis technology. Wearable technology is a fast-growing industry, and the improvement of existing human motion analysis tools is needed. Prior research has proven the viability of SRSs as a tool for capturing motion of the foot-ankle complex; this work covers extensive effort to improve and ruggedize a lab tool utilizing this technology. The improved lab tool is validated against a camera-based motion capture system to show either improvement or equivalence to the previous prototype while introducing enhanced data throughput, reliability, battery life, and durability.

Key words: soft robotic sensors, wearable devices, validation, ankle joint complex, linear regression, kinematics
DEDICATION

I dedicate this thesis to Sally Kate, my wife.
ACKNOWLEDGEMENTS

I am greatly appreciative to the many people part of the Athlete Engineering group at Mississippi State University who have made this research possible. I thank David Saucier for coordinating lab training and usage for data collection and experiments. I thank Alana Turner, Purva Talegaonkar, Carver Middleton, and Erin Parker for help with experiment data collection and participant preparation.

I thank Preston Peranich, and again Carver Middleton and Erin Parker for help designing and fabricating the many iterations of the sock prototype. I am thankful for their contributions in firmware testing and development, enclosure design and fabrication, electronic component assembly, and sock design and sewing/fabrication.

I thank all principle investigators (PIs) working with the team for their expertise and direction throughout the process of designing and validating the prototype. These PIs include Dr. Harish Chander, Dr. Adam Knight, Dr. Raj Prabhu, and Dr. Brian Smith.

I express great thanks to my academic advisor, Dr. John Ball, and the lead PI for the project, Dr. Reuben Burch. Their willingness to invest in their students and peers is unmatched and is beneficial to everyone with whom they work.

The research presented in Chapters 3 and 4 was funded by the National Science Foundation under NSF 18-511 — Partnerships for Innovation Award Number 1827652. The findings and opinions presented in this thesis belong solely to the author and are not necessarily those of the
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CHAPTER 1
INTRODUCTION

The Athlete Engineering group at Mississippi State University (MSU) began as a small team motivated by the desire to improve the current state of wearable technology. Through a series of interviews and market research it was discovered that strength and conditioning (S&C) coaches across sports, geographical locations, and competitive levels distrusted most wearable devices because of fundamental inaccuracies in the information they report [60]. Improvements in wearable kinematics tracking and performance evaluation sensing would have the potential to help coaches and practitioners in many athletic departments; additionally, these benefits could be reaped by organizations beyond athletics such as industry, medicine, and the military. Research kicked off and continues through the time of this writing with a project funded by the National Science Foundation Partnerships for Innovation (NSF-PFI) program. This research effort has worked toward a wearable device capable of capturing motion of the human foot-ankle complex [62]. Today, the Athlete Engineering group involves over 50 people including students, professors, and athletic staff spanning backgrounds of engineering, kinesiology, fashion design, sports science, and many more.
1.1 Motivation

This thesis continues and extends the research efforts of Saucier et al. [78, 77] in developing a foot-worn garment for motion capture replacement. This research aimed to bring the sock prototype and data analysis methods developed in the aforementioned research multiple steps closer to a marketable product as is the purpose of the NSF-PFI program. The use of soft robotic sensors (SRSs) as a substitute for more traditional motion analysis sensing techniques is integral to the success of this research and is a core feature of the wearable system.

1.2 Contributions

The contributions of this thesis to the team research effort include:

- Planning, coordinating, and executing experiments and data collection sessions (discussed in section 4.2).
- Designing and implementing embedded hardware, firmware, and software systems to enable experiments (discussed in section 3.4).
- Developing software tools to collect, store, and analyze experiment data (discussed in sections 3.3 & 3.4.5).
- Organizing and maintaining open source repositories to share code, designs, and sample data with the public (discussed in section 3.1.3).
- Co-authoring journal and conference papers to present the results of this research (discussed in section 1.3). (First author: 1, Co-author: 4)
- Management of a small team of students working together to build and improve prototypes.

1.3 Publications

This thesis contains content from the following publications:

Other publications which I have contributed to as a co-author include:


CHAPTER 2
BACKGROUND

This chapter explains high-level concepts necessary for understanding the work presented in this thesis. The goal is to help the reader attain a basic understanding of foot-ankle kinematics, motion capture, soft robotic sensors (SRSs), some important signal processing techniques, and the general statistical methods used for analysis.

2.1 Foot-Ankle Kinematics

Kinematics refers to the “description of motion, including consideration of time, displacement, velocity, acceleration, and space factors of a system’s motion” [28]. Kinesiologists and S&C practitioners use kinematics to interpret the movements of patients and athletes; understanding the details of the way an action is performed can lead to important insights about strength and skill, potential for or history of injury, and rehabilitative training for the future. The research in this thesis is concerned with modeling kinematic details of the human foot and ankle. A simple model describes the foot as moving in two planes about the ankle — the sagittal plane and frontal plane [28]. The sagittal plane angle describes the angle at which the foot is “pitched” toward or away from the knee (see figure 4.1 on page 49 in section 4.1.1 for an illustration), while the frontal plane angle describes the angle at which the foot is “rolled” inward or outward (see figure 4.2 on page 50 in section 4.1.1 for an illustration) [28].
Four movements can occur within these two planes of motion. Within the sagittal plane, plantarflexion refers to the rotation of the foot away from the knee and results in the sagittal rotation angle becoming more negative [28]. Dorsiflexion refers to the opposite movement, rotating the foot toward the knee, and results in the sagittal rotation angle becoming more positive [28]. Similarly, inversion and eversion refer to the rotation of the foot inward (more positive angle) or outward (more negative angle) from the midline, respectively [28].

2.2 Motion Capture and Wearable Devices

Motion capture refers to the usage of any system capable of recording motion in 3D space to store and later use motion data. In biomechanics research, motion capture is used extensively to view and analyze human movement [98]. Camera-based 3D motion capture systems are seen as the “gold standard” in motion research because of their accuracy [98]. The motion capture system used in this research is a 12-camera system using Vicon™ Bonita infrared cameras (Vicon, Oxford, UK). This system precisely tracks the position and orientation of small retro-reflective markers affixed to the human subject. Markers are fixed to the subject’s limb segments of interest and this marker positive information is streamed to a software application called TheMotionMonitor xGEN (Innovative Sports Training, inc., Chicago, IL). After a short calibration procedure, this software interprets the marker locations to track a model of the subject’s skeletal joint angles. These joint angles can be exported for later analysis.

2.2.1 Wearable Devices

The ability to build electronic devices with tiny embedded computers and sensors has spawned an entire industry of wearable devices. Wearable devices include devices containing portable
computers with sensor suites designed to provide desirable information about human activity or health [15]. The subject of this research is the development of a wearable ankle joint motion capture system. Wearable devices which measure any kind of motion are often validated using a camera-based motion capture system before the data output of the device can be trusted [73].

2.3 Soft Robotic Sensors

Soft robotic sensors (SRSs) are a class of (typically) passive sensors that respond in some electrical characteristic to changes in deformation to measure physical characteristics such as strain, stress, surface features, and more [87]. SRSs have many potential applications in robotics, materials science, and wearable technology. The SRSs used in this thesis are manufactured by StretchSense™ (Auckland, New Zealand) and are of the capacitive variety – meaning they respond positively to increased strain with an increase in electrical capacitance.

2.3.1 Capacitive Soft Robotic Sensors

Capacitive stretch sensor designs leverage the effect of the geometry of two parallel plates on electrical capacitance. Equation 2.1 describes the capacitance of a capacitor composed of two parallel plates with area $A$ separated by a dielectric layer with thickness $d$; $\epsilon_r$ and $\epsilon_0$ refer to the electric field permittivity of the dielectric material and free space, respectively [93, 40].

$$C = \frac{\epsilon_r \epsilon_0 A}{d}$$ (2.1)

Because both the conductive plates and dielectric are made of pliable materials, inducing strain on the sensor causes both the area $A$ and dielectric thickness $d$ to change, influencing the
capacitance of the sensor [47]. The capacitance at any given point in time can be measured using any common capacitive sensing method.

2.4 Signal Processing Techniques

Preparing experimental data for statistical analysis required processing of the recorded samples. Because of the time-series nature of this data, standard signal processing techniques apply.

2.4.1 Savitzky-Golay Filtering

All signals sampled from the real world contain some level of noise; noise is unwanted information in a signal caused by random effects of the environment or interference from competing signals. Because of this, signal filters exist to remove information from a signal based on some criteria — typically frequency content. The filter used in this research is called the Savitzky-Golay filter, a non-causal low-pass filter derived from the least-squares approximation method [79]. A sliding window is moved along a signal, and a polynomial least-squares approximation of the points in the window is used as the output for each point. The Savitzky-Golay filter excels at reducing high-frequency noise while preserving signal shape and peak values [79].

The frequency response properties of the Savitzky-Golay filter have been characterized [80]. Equation 2.2 was used in this research to implement a Savitzky-Golay filter with a predetermined cutoff frequency where \( f_c \) is the cutoff frequency normalized by the sampling frequency, \( N \) is the order of the filter, and \( M \) is the window half-length.

\[
f_c = \frac{N + 1}{3.2M - 4.6}
\]  

(2.2)
2.4.2 Cross-Correlation and Alignment

Data collected during an experiment comes from three independent devices: the motion capture PC, the left foot sensor electronics, and the right foot sensor electronics. Because the clocks of each of these devices cannot be tightly synchronized, the time-series data must be aligned during data preprocessing.

The cross-correlation function scores the similarity between two signals at varying lags between the two signals. Equation 2.3 defines the cross-correlation of two discrete-time functions $f[m]$ and $g[m]$ as a function of the displacement lag $n$ [21].

$$ (f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]g[m + n] \quad (2.3) $$

After calculating the cross correlation of the two functions, the lag with the best similarity score can be selected using Equation 2.4. Cross-correlation alignment aligns the signals based on their point of best similarity; use of this method requires the assumption that the best alignment lag for synchronizing two signals is the point at which they are most similar. This assumption is made for the research in this thesis because stretch sensors in the current prototype and the camera-based motion capture system used as ground truth are similarly shaped.

$$ n_{\text{best}} = \text{argmax}(f * g[n]) \quad (2.4) $$

2.5 Statistical Methods

Several statistical methods were employed for comparing the accuracy of the stretch sensor measurements to the outputs of the motion capture system. The first of these, linear modeling,
allows transformation and fitting of the raw sensor values (measured in picoFarads) to the same units as the motion capture system, degrees. The second, significance testing, allows mathematical evaluation of variances in sample sets to determine if a perceived change in performance is significant.

2.5.1 Linear Regression

Linear regression allows the calculation of optimal coefficients for a set of data using linear combinations of inputs [46, 57]. It may be used to predict a single output dependent variable as a function of any number of independent input variables. In this study, single and multiple linear regression are used to map stretch sensor values to an estimated joint angle. Equation 2.5 describes a linear equation with coefficients and an intercept which can be optimally calculated to predict a dependent value \( y \) as a function of a set of \( N \) linearly combined variables \( x_1 \ldots x_N \).

\[
y = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_N x_N
\]  

(2.5)

Several scoring metrics are used to evaluate the performance of the model: coefficient of determination (\( R^2 \)), root-mean-square error (RMSE), and mean absolute error (MAE). \( R^2 \) describes a statistical goodness of fit and is calculated using the residual values of the estimation, and a higher number is better. RMSE describes an average expected error between two signals; MAE is a similar metric to RMSE, but does not penalize large errors as heavily as long as they are of short duration. For the RMSE and MAE metrics, a lower number is better.
2.5.2 Statistical Significance Testing

Statistical significance tests are a method used often in published research to determine with high probability that a result is repeatable. Significance tests often focus on $p$-values, the probability of a particular result given a certain hypothesis [86]. A commonly accepted threshold for $p$-value significance is 0.05. Different tests are appropriate for different types of data samples. In this research the Welch’s t-test was used because it allows two sample sets to have different standard deviations [90]. Because the focus of this research was to improve the reliability of the existing sock prototype, equal standard deviations in mean accuracy scores could not be assumed.
CHAPTER 3
PROTOTYPE AND METHODOLOGY IMPROVEMENTS

3.1 Introduction

Feedback plays an important role in sports as real-time adjustments in training methods based on performance can help both coaches and athletes enhance output while mitigating the risk of injury [11]. Due to the employment of varying training techniques used across multiple baselining and recovery philosophies, multiple sports, and varying levels of competition, ambiguity can arise in how to best develop training in order to optimize the performance of an athlete. Regardless of the programming paradigm, a central need for strength and conditioning (S&C) coaches is the ability to define performance improvements objectively [60]. For this reason, data collection has long been a part of the daily routine for S&C coaches. Initially, these data collection methods involved manual reporting and subjective observation. However, widespread adoption of sports monitoring devices, such as wireless wearable sensor systems that offer valuable insight into athlete performance, are changing the methods utilized by S&C coaches regardless of their coaching philosophy [60]. By using wearables to capture and then examine performance data in near real-time, it is possible to provide the coach or athlete with immediate feedback, enabling coaches to adjust training programs such that they enhance workload output while mitigating the athlete’s future risk of injury [20]. Regardless of the tool and method used for data collection, the quality of the information is often the limiter for coaches looking to make genuinely informed decisions [13].
3.1.1 Athlete Data Collection Limitations

Understanding sports biomechanics is critical for mitigating injury risk and improving performance. Movement biomechanics are traditionally evaluated using optical systems, the gold standard method for motion capture [89]. These motion capture systems, however, are generally constrained by their capture volume due to camera set-up and are usually restricted to laboratory environments. Additionally, reflective markers take time to mount and can impede the performance of the tasks under investigation. Conversely, the complexity of the movement and task being assessed often leads to marker occlusion [72]. Wearable technology is an alternative approach to camera-based motion capture with the potential to overcome these limitations. Wearable systems can provide real-time feedback within actual sports environments and during live training and competitions—a feature not easily accessible through video analysis. Wearable systems are designed to be compact, lightweight, wireless, portable, and unobtrusive to facilitate maximum mobility while being used during a task, thereby allowing for monitoring of athletes outside of a laboratory setting and in their natural environment [3]. There are several types of sensors, namely, inertial measurement units (IMUs) and micro-electromechanical sensors (MEMs). These include a combination of accelerometers, magnetometers, and gyroscopes used to collect biomechanical measurements. Wearable sensors are now the most commonly used data collection system in several different sports, such as swimming [27], snowboarding [50], baseball [48], rowing [10], skiing [68], netball [84], football [2, 9], rugby [9], and general athletics [71]. Despite the increasing utilization of wearable sensors in sports, they do present usage limitations. Ferromagnetic objects in the vicinity of wearables can alter measurements from inertial-based systems. Inaccurate positioning can impact both data precision and integration, further resulting in errors during the extrapolation of
positional data from acceleration measures. Accuracy is further brought into question as certain movements may lead to unnecessary or noisy data, sensor displacement, or general failure of the sensors and their connections to the data capturing devices [33, 52]. Soft robotic sensors (SRS), a novel system of sensors that measure strain and can be used to collect movement measurements when stretched across a joint axis, may provide an alternative to the use of IMUs mounted on rigid circuit boards. SRS can be described as a textile-based conductive material sensor technology with electrical properties that change when subjected to mechanical deformation [52]. When properly placed on the human body across a joint, stretching or flexing an SRS will cause a geometrical change that induces an equal, linear response in the electrical properties, allowing these sensors to detect and quantify motions, such as the flexion and extension of fingers, elbows, or knees [33].

3.1.2 Origins of Closing the Wearable Gap Research

In June 2017, a National Science Foundation (NSF) Innovation Corps (I-Corps) training site pilot grant funded an investigation on new athletic wearable technology. A series of interviews were conducted around the country with S&C coaches and athletic trainers for both men and women sports at the collegiate and professional level. According to the responses from the I-Corps interviewees, there were trust concerns regarding the data from the wearable sensors due to consistent inaccuracies and lack of transparency regarding how correlations were being made. Besides, these wearable sensors failed to capture preferred movement information (such as ground reaction forces and foot-ankle complex movements) [60, 62]. The intent of the “Closing the Wearable Gap” paper series was to determine whether SRS could be repurposed for motion capture through a custom-made wearable application. The motivation behind this study was to eliminate
the problems found by IMU-based wearable solutions, such as drift. With a clear goal provided by athletic practitioners to capture data “from the ground up”, the paper series aimed to evaluate the use of SRS to measure kinematic and kinetic data at the foot-ankle complex. Capturing foot-ankle complex movements in near real-time as the mobility of the foot and ankle influences the closed kinetic chain of the lower body and, ultimately, human movement as a whole was the focus of this research [42]. This SRS-based solution has many advantages for both the athletic and rehabilitation industries as an excessive movement beyond the normal range of motion can result in ankle sprains [19, 36]. Applying SRS at the foot-ankle complex may help provide information to the coaches, trainers, and therapists to aid in preventing injuries and validating proper ankle rehabilitation and training exercises. The advancements in the field of SRS may also be applicable to “industrial athletes”. The term “industrial athlete” applies to anyone who earns a living through intellectual and physical abilities, performing jobs involving motor skills that require motor abilities, such as strength, flexibility, coordination, and endurance—much like a sports athlete [5]. Industrial athletes often perform repetitive motion tasks over the course of multiple hours, and, when performed improperly, this can lead to musculoskeletal disorders and, in turn, may need the same level of attention as a sports athlete from a rehabilitation team [82]. Advancements in SRS technology can be used to help athletes of all types by monitoring parameters associated with injury risk, continuous health, and well-being.

3.1.3 SRS Validation Gaps

Soft robotic sensors are thin, strap-like electronic sensors that respond to mechanical deformations and, when stretched, create a linear voltage shift, measured either in resistance or
capacitance. Research and development of SRS in both academia and industry have seen a recent increase [18, 25, 44, 53, 56, 96, 49, 95, 83]. Numerous efforts have been made to develop flexible, stretchable, and sensitive SRS due to the potential diversity of their applications, such as rehabilitation and personal monitoring [16, 30, 34, 17, 58], structural health monitoring [24, 45, 54, 97], sports performance monitoring [20, 52, 34, 35], human motion capture for entertainment systems [59, 74, 92], and mass measurement [94]. Depending on the type of material and manufacturing processes, the sensors react to the applied strain with different response mechanisms. Linearity is an essential response parameter of SRS as it provides consistency and precision to signal detection. Linearity relates to the relation between the relative shift of the electrical signal and the strain applied, which, if truly linear, can be represented graphically as a straight line. The linear working range of the SRS depends on the textile substratum properties and how the conductive components have been integrated into the textile [4, 55]. Though there has been advancement in testing and development of new wearable SRS with different substrates for health monitoring and human motion detection, there is little information available related to linearity testing tools. Most efforts have been devoted to improvements in sensing performance, sensor applications, and manufacturing processes. Electromechanical tests have been conducted by attaching the sensors to off-the-shelf, commercially available motorized testing stages/machines, universal testing machines, or motion controllers, which apply cyclic stretch/strain to the sensors with electrical responses recorded using a multimeter [92, 4, 55, 12, 32, 39, 65, 67, 88]. Some experiments include manual stretching and relaxation of SRS over multiple cycles with changes in its electrical values recorded using a digital multimeter [17, 59]. Because there is little in the way of standardized benchmark testing for SRS, this gap is addressed by developing a custom stretch sensor tool kit (SSTK) to capture sensor
characteristics during foot-ankle complex movements, as detailed in Section 3.2. Furthermore, as discussed previously, the purpose of the Closing the Wearable Gap series was to take these new types of sensors (SRS) and determine if the solutions developed by the research team can be repurposed for motion capture via a customized wearable technology application. For this research paper series, verification and validation studies were performed and documented to establish confidence in the capabilities of the linearity of these SRS sensors and methodologies developed to test them.

Mississippi State University’s (MSU’s) Athlete Engineering research team was funded by NSF to design and develop wearable devices using SRS to capture the kinematics and kinetics of human movement. Throughout the process of validating the use of SRS to collect this data, multiple methods to validate SRS electrical properties, enhance data analyses, and establish ideal SRS mounting designs have been developed. This thesis outlines the steps taken toward sensor validation and the iterations developed for testing methodologies and introduces the newest sock prototype for human subject experiments based on lessons learned from previous experiments. This progression will be viewed from the aspects of (a) materials testing of the SRS, (b) automation of the data analysis software, and (c) development of the hardware and software prototype. All SSTK solutions developed for this NSF initiative are shared on GitHub and linked from Table 3.1 on the following page.

1https://github.com/msstate-athlete-engineering/soft-sensors-research
2https://github.com/msstate-athlete-engineering/soft-sensors-research/tree/master/openSRS-manager
3https://github.com/msstate-athlete-engineering/soft-sensors-research/tree/master/openSRS-labkit-v1
4https://github.com/msstate-athlete-engineering/soft-sensors-research/tree/master/gait-biomechanics-tools
5https://github.com/msstate-athlete-engineering/soft-sensors-research/tree/master/gait-biomechanics-tools
6https://github.com/msstate-athlete-engineering/soft-sensors-research/tree/master/datasets
Table 3.1

GitHub location of all SSTK solutions developed as part of the Closing the Wearable Gap paper series.

<table>
<thead>
<tr>
<th>Item (Hyperlink)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft Sensors Research Repository¹</td>
<td>Publicly available GitHub repository used to distribute and showcase hardware/software tools to the community (contains items listed below).</td>
</tr>
<tr>
<td>openSSTK-manager GUI²</td>
<td>A software tool used to communicate with/control custom hardware, assist with lab data collection, and visualize/export data.</td>
</tr>
<tr>
<td>openSSTK-labkit-v1 Hardware/Firmware³</td>
<td>PCB design files, 3D case models, and firmware source code for custom lab data collection kit.</td>
</tr>
<tr>
<td>Biomechanics Data Analysis Scripts</td>
<td>SRS/MOCAP data analysis using general statistical techniques.</td>
</tr>
<tr>
<td>(Statistical)⁴</td>
<td></td>
</tr>
<tr>
<td>Biomechanics Data Analysis Scripts</td>
<td>SRS/MOCAP data analysis using deep learning/machine learning techniques.</td>
</tr>
<tr>
<td>(Deep Learning)⁵</td>
<td></td>
</tr>
<tr>
<td>Publicly Available Datasets⁶</td>
<td>Deidentified raw experiment data for public use.</td>
</tr>
</tbody>
</table>

Figure 3.1 on the next page represents a visual timeline of the three components developed for the SSTK in terms of SRS validation and laboratory experiments. All the elements presented in Figure 3.1 on the following page can be found in sequential order in the narrative.

3.2 Material Testing Tools

One of the initial goals of the Closing the Wearable Gap series was to validate that the electrical output of the SRS changed linearly when stretched under different simulated ankle movements [62].

3.2.1 Tilted Surface Platform

Once the initial experiment using the wooden ankle model was completed, a study using human subjects was conducted where optimal placement and orientation configuration (POC) on the ankle
Figure 3.1

SSTK (stretch sensor tool kit) development timeline, depicting the three elements of SRS (soft robotic sensors) validation and SRS-based wearable development: materials testing, data analysis software, and data collection hardware/software.
joint complex was determined [78]. The details of the mounting methods for the SRS onto a sock have been discussed later in this narrative. Once optimal POCs were determined for each of the four foot-ankle complex movements (PF, DF, INV, and EVR), trials were conducted, validating the accuracy of SRS to predict kinematic data during gait [77]. To perform the gait trials, two different walking platforms were created: flat surface and tilted surface platform (TSP). When walking on level ground or a flat surface, PF at the heel strike continues until the onset of midstance, and progressive DF occurs from heel off until 40% of the cycle when PF begins again. During the swing phase, the DF of the ankle joint occurs until the heel strike [14]. Multiple gait biomechanics studies state that the motions of PF and DF are the major contributors to overall ankle motion when walking on even surfaces. The average PF and DF range of motion of the ankle have been measured at 40°–56° and 13°–33° on a flat surface, respectively [14, 23, 63, 26]. Since walking on a flat surface does not induce significant EVR and INV at the foot-ankle complex, the TSP was constructed so that a greater ROM for INV and EVR could be recorded for the participants during self-paced gait cycles. An example of a participant walking across the TSP is shown in Figure 3.2 on the next page.

The TSP designed for the study was derived from a walkway built for a railroad ballast surface in which the similar participant’s INV and EVR for rearfoot motions characteristics were studied [51]. The TSP was a 1.22 m wide, 7.32 m long wooden framework with a mass of more than 54.43 kg. The mass of the TSP prevented it from slipping during the participant trials. The platform walkway was tilted at 10° to increase the INV and EVR motions of the foot-ankle complex during gait cycles. The surface angle for the TSP was validated using a digital bubble level application on an iPhone. The flat surface and the TSP were placed parallel to each other. Both surfaces were
Participant walking across a tilted surface platform (TSP).

covered with the same type of rubber mats to avoid confounding variables on the walking surface. Because of the motion asymmetry created by the transverse slope, participants were asked to walk in both directions along with the inclined surface platform. Additional details on the dynamic gait experimental procedures and testing can be found in Closing the Wearable Gap Part IV [77]. The TSP was able to successfully augment the ROM of INV and EVR while participants walked across it. However, one challenge that arose from the construction of the TSP was that the platform itself was large, heavy, and difficult to move around. This meant that the TSP had to essentially remain in place for the entirety of the experiment. This imposed limits on how the TSP, along with the flat surface, was arranged for the experiment. Lastly, a challenge common to conducting gait analysis with motion capture, a limited capture space, had to accounted for. While tilted walking
for long durations will not be feasible, future gait studies conducted on a treadmill would permit
the collection of a larger amount of gait data more quickly without the need to continuously check
to ensure the motion capture system is properly tracking the participant.

3.3 Data Analysis Software

To validate the proposed testing tools as well as the sensor mount designs introduced in Parts
II-IV and Part VI of the Closing the Wearable Gap series, data analysis had to be conducted for
numerous trials. A large portion of this process was automated through the writing of scripts in
R and MATLAB to handle the preprocessing. These scripts were designed with the intention of
further use and optimization in later experiments.

3.3.1 Simple Linear Modeling Analysis for SRS Placement on the Foot

Closing the Wearable Gap Part II focused on determining the optimal POC of SRS mea-
urements using human subjects who performed foot movements in a seated, non-weight bearing
(NWB) position. The data collected was validated against kinematic data collected from a 12-
camera motion capture system. The POC considerations for the SRS have been discussed in detail
in the results section of the Part II paper [78]. The foot-ankle complex kinematic data for each
degree of freedom were determined using the MotionMonitor™ software’s Grood–Suntay angle
orientation. The raw values of the SRS were measured using a Bluetooth-enabled microprocessing
unit, which connected to the SRS through a serial peripheral interface (SPI). Several pre-processing
procedures were performed to compare the data between MotionMonitor™ and the SRS. One of
the issues faced was that the 3D motion capture data was sampled at 100 Hz, while the SRS data
was sampled at approximately 25 Hz. Further, the samples collected for the SRS were not evenly
spaced over time due to limitations of the smartphone application. To mitigate this issue, an R approximation function was used to interpolate the SRS value based on the timestamps collected from MotionMonitor™, bringing the sensor data up to 100 Hz. After approximating the sensor outputs, data was aligned over time with the motion capture output as there were slight delays observed due to manually starting the data recording on each measurement system. This was overcome by using the cross-correlation technique, which measures the similarity between two signals based on a time shift [76], aiding in the determination of the proper data time alignment. The time alignment was based on the movement performed during the trial. Once the data was properly formatted, a linear model based on the output of the sensor versus the kinematic motion capture data to provide a measure of how well the SRS modeled the data of motion capture was created. Furthermore, the MotionMonitor™ data was recorded in two columns (sagittal plane (PF/DF) and frontal plane (INV/EVR) joint angles), whereas the SRS data was recorded in four columns (PF, DF, INV, and EVR). For certain sensors to properly model the motion capture data, the dataset needed to be flipped; that is, PF and EVR were recorded as negative changes in MotionMonitor™, but they were recorded as positive changes in the SRS data. If PF or EVR movements were being performed, the MotionMonitor™ data had to be inverted for the positive linear relationship between two datasets to be maintained. The analysis process for this study was implemented in R.

3.3.2 Multiple Linear Modeling Analysis for Gait Analysis

Closing the Wearable Gap Part IV focused on comparing SRS wearable solution data based on 3D motion capture while participants walked across flat and sloped surfaces [77]. The purpose of this study was to examine SRS‘ success in modeling the kinematic data at the foot-ankle complex
during participant gait cycles. A similar methodology for data preprocessing was undertaken as in Part II [78], where SRS data was upsampled, and cross-correlation was used to align the data. For gait correlation, a Savitzky–Golay filter was applied to smooth the SRS data and adjust for aliasing when upsampling the data. Individual gait cycles were extracted from each of the trials. Analysis was performed using individual linear models, analogous to Part II, where one sensor was used per foot-ankle complex movement [78]. It was realized, however, that this approach was not a practical method of analyzing the gait assessments as it led to poor results. Multiple joint actions of the foot-ankle complex take place concurrently during the gait cycle. Because of this simultaneous motion of the foot-ankle complex and the sensor placements, a coupling of movements occurred, in which the sensor was affected by the movements they were not positioned to measure. This is a natural occurrence of the tri-planar movement that takes place at the foot-ankle complex, defined as supination and pronation. A multivariable linear model was developed to address this issue, improving the prediction accuracy of the motion capture data ($RMSE = 1.96^\circ, R^2 = 0.854$) [77]. All four SRS sensors on each foot were then used to predict the output of the sagittal plane and frontal plane movements. Combinational experiments were conducted, utilizing multivariate regression models to understand how much data would be lost on the removal of different sensors. Using these combinational methods, several models were developed, including one where PF and DF sensors were used to predict sagittal plane motion, while the INV and EVR sensors were used to predict frontal plane motion. Other models were generated, with each sensor being removed individually. The goal behind the individual elimination of each sensor was to understand if any sensor data was redundant. However, looking at the results obtained on the removal of sensors, the research team preferred to move forward with the one-to-one ratio of sensors on the primary
foot-ankle movement. The results for each of the sensor combinations investigated are outlined in Part IV [77]. Another challenge introduced during the gait analysis for Part IV was the desire to analyze the trials as individual gait cycles [77]. Every trial needed a minimum of two gait cycles, and some trials also contained a third gait cycle if the participant was still in the capture space of the motion capture system. Each gait cycle, as discussed previously, is defined as the data collected from the first heel strike of the specified foot to the second heel strike of the same foot. Unfortunately, there was no way to automate this using the kinematic data from the motion capture system. Each trial had to be replayed manually to note the timestamps at which every heel strike occurred. An additional R script was developed to read these values and trim the data files accordingly so that they could be analyzed as individual gait cycles. This contributed to the decision to attach pressure sensors to the next sock prototype at the heel so that the heel strikes would not need to be manually identified in post-processing, and the notation of gait cycles could be automated.

3.3.3 Deep Learning Methods for Gait Analysis

When analyzing the data for Part IV, it was found that the output of the SRS was coupled with multiple movements of the foot-ankle complex. This led to the conclusion that the output of the SRS mounted on the foot could change due to stretch along one or more planes of movement. More advanced modeling approaches were investigated to address this issue. In Closing the Wearable Gap Part VI, the gait data collected from the Part IV study was revisited to evaluate the model’s accurateness and validity using deep learning methods [22]. To establish more accurate models, both linear and nonlinear relationships between SRS and 3D motion capture measurements were
investigated. Moreover, to assure the validity of developed models on the new data, the models were trained with a subset of the dataset using $k$-fold cross-validation. In this study, three different approaches—(a) multivariable linear regression, (b) artificial neural network (ANN), and (c) long short-term memory (LSTM) network—were applied to investigate the SRS functionality in capturing foot-ankle complex movement against the 3D motion capture system. Prediction models were developed to approximate the sagittal and frontal plane joint angles of the ankle obtained from the motion capture system. The multivariable linear regression from the Part IV study was included to be compared to the new techniques introduced in the Part VI paper. The ANN and LSTM network investigated the more complicated and nonlinear relationship between the SRS and motion capture data. The models were developed for each participant separately, and the network architectures were designed to fit the specific walking pattern of each individual. Further details on the implementation of these deep learning approaches can be found in [16]. In the Part VI study, feed-forward neural networks with backpropagation were developed, and different network architectures were tested on the dataset for each participant, with different input-output combinations to determine the best fit for each one. Networks with one and two hidden layers using 1 to 10 neurons were tested. The input layer consisted of four neurons designed for input attributes, including data received from the four SRS placed on the socks. These input variables were fed into the neural network for training the weighted vectors of the network, and the output of the neural network was the prediction of the 3D motion capture data. The output layer consisted of one neuron, producing the output of the network. The authors developed an LSTM network with six layers, including an LSTM with 125 hidden states, a dropout layer with a 50% dropout rate, followed by another LSTM layer with 100 hidden states and another dropout layer with a 50%
dropout rate, a fully connected layer, and a regression layer. The authors developed eight different models for each participant to analyze the relationship between the SRS capacitance measurements (PF, DF, INV, and EVR) with the sagittal plane and frontal plane outputs of the 3D motion capture system on both feet during the gait movement on two walking surfaces (flat surface and TSP). The models were trained and tested using $k$-fold cross-validation. Due to LSTM’s complexity, many architectures to find the best-fitted architecture for each participant were not able to be designed or applied. However, doing so might improve the LSTM performance. Results indicated that the ANN model performed the best (average RMSE = 3.63), while the multivariable linear regression and LSTM models performed modestly (average RMSE = 3.94 and = 3.98, respectively) [22].

3.4 Data Collection Devices

Throughout the Closing the Wearable Gap series, the mounting method for the SRS was iteratively improved, as well as investigated how to best measure and collect data.

3.4.1 Initial Microprocessor Testing

Traditionally, biomechanical data collection is often confined to a research laboratory due to the requirements of the equipment for optical motion capture. One of the purposes of this research was to take SRS and determine whether they can be repurposed for motion capture, outside the laboratory settings, via a customized wearable sensor technology application for collecting real-time data. To collect real-time data, a basic microcontroller-based prototype was created to collect data from four SRS at one time. For the Part I paper, this prototype consisted of an Arduino Uno R3, an ADS1116 16-bit analog to digital converter (ADC), and an array of four voltage divider circuits. The ADC module, being low-power, precise, and I2C-compatible, has an incorporated
programmable gain amplifier (PGA) and a digital comparator, along with a wide operating supply range, making ADS1116 well suited for sensor measurement applications. The PGA offers an input range from ±256 mV to ±6.114 mV, enabling precise large- and small-signal measurements. The ADC module was thus able to detect small voltage changes, useful for increasing sensitivity to changes in stretched sensor lengths. This initial prototype gave an idea of how to collect measurements from multiple SRS. Due to the ADC and voltage divider circuits being connected via a breadboard, it was believed there was some noise introduced that would be mitigated via a custom printed circuit board (PCB) design. Some difficulty with measuring multiple sensors accurately was encountered as each SRS had a different electrical output without being stretched, despite being the same length. This led to the decision to use a voltage divider circuit to measure the SRS, as it could better handle a range of values among different SRS. When compared to the Agilent™ micro-ohm meter, the computing unit had an average percent error of 1.55% [62]. More details on the design decisions and implementation of this prototype can be found in [62].

3.4.2 Sock Prototype: Iteration I

Closing the Wearable Gap Part II tested the reliability of the SRS for foot movements by mounting the SRS on the foot-ankle complex of 10 participants in an NWB, sitting position. The purpose of the study was to examine various SRS placements and orientations by using four SRS to measure foot movements and validate against motion capture data [78]. The end goal of this research was to create a fully SRS-integrated, sensor-laden compression sock, which could be used for future trials. INV, EVR, PF, and DF were tested individually to choose appropriate POC for sensors configured to monitor each type of movement. Each participant wore a specialized
compression sock from which the SRS could be tested consistently for all POCs for each participant [14, 61]. Mounts needed to be built for the sensor to attach them to the socks, while still being able to easily shift the sensors to different POCs between trials. This led to the use of Velcro mounts, which would enable them to quickly remove and attach sensors to participants and provide consistency of placement and orientation across trials. E6000 clear adhesive was used to attach the Velcro to the socks because the adhesive did not work well enough when the sensors were stretched, sometimes causing sensors to fall off the sock. Although the concept worked well enough for the experiment, the use of superglue and multiple Velcro mounts made the sock stiff and difficult to don and doff. As the analysis involved comparison with the 3D motion capture system, it was imperative that the motion capture reflective clusters could be mounted over the sensors to monitor joint angles. Athletic straps were wrapped around the foot and shank for mounting the clusters. Figure 3.3 on the following page shows the initial attempts to use Velcro to attach the sensors to the sock to conduct the studies of placement and orientation configurations.

Closing the Wearable Gap Part III focused on validating the use of SRS during an unexpected and expected slip and trip perturbations to detect foot-ankle complex kinematics. Only PF and DF along the sagittal plane for the data collection was measured. One of the problems faced when performing the experiment with the sock prototype was the need for a stable enclosure to accommodate the SRS module. The athletic strap wrapped around the participant's shank was used as a mount for the sensor module and battery pack (shown in Figure 3.4 on page 30). Since the study included a treadmill that induced the perturbations for the slip and trip, the jerking motion that occurred during the slip and trip would sometimes loosen the strap, and the module would have to be remounted.
Figure 3.3

Early attempts at using Velcro to attach sensors to the sock. (a) The initial attempt at mounting SRS with Velcro, (b) SRS mounting SRS to ankle straps with Velcro on SRS only, (c) SRS mounted with motion capture clusters and sensing module, and (d) SRS mounted while the foot is being calibrated to the neutral position.
Figure 3.4

A sock prototype was used for the slip and trip experiment. SRS module location in the red circle.
3.4.3 Sock Prototype: Iteration II

For the gait study performance in Part IV, an enclosure was designed and 3D printed to avoid the strap loosening issue for future experiments (Figure 3.5) [77]. The enclosure would house both the sensor module and the battery pack. The enclosure to included loops for the athletic strap to run through, allowing it to be easily mounted on the shank of the participant. This resolved the issue of the module falling or loosening during jerky movements. These arrangements, however, still had some disadvantages. There was an abundance of wiring from the sensors that had to be wrapped and tucked behind the athletic straps to avoid disruption to the participants during the trials. Adding to this, the Velcro, which was superglued to the socks, as described previously, created difficulty in donning and doffing of the sock, which resulted in damage to the socks. These problems led to the development of new methods of sensor mounting for future studies and a new prototype of the sock.

![Figure 3.5](a) Second sock prototype iteration; (b) 3D printed enclosures circled in red in the right image.
3.4.4 Sock Prototype: Iteration III/Current

The most recent iteration of the sock prototype addressed several problems with super gluing the Velcro and sensor mountings to the sock. As seen in Figure 3.6 on the next page, a hook-and-eye method was utilized for connecting the sensors to the sock. This made it easier to mount and detach the sensor from the sock as the Velcro would get attached to and sometimes damage the sock. A band was used to secure the sensors, prevent them from moving during participant trials, and make the SRS flush with the natural curvature of the ankle joint. Initially, paper backing was used to attach the hooks on the socks, which, although useful, was not strong enough to withstand multiple movements caused during the tests and continuous donning and doffing of the sock. To attach the 3D printed enclosure to the sock button snaps were used. One-half of the snaps were attached to the case of the enclosure, and the second half was attached near the top of the sock. The hook and eye attachments, paper backing, and the button snaps were all hand-stitched onto the sock. The paper backing had been replaced by a woven cotton cloth, stiffened with fusible interfacing. Compared to the paper backing, the cotton fabric backing was even more durable and could withstand further movements and multiple participant tests. This cloth backing, on the top part of the sock, was sewn using a zigzag stitch on a sewing machine. The bottom backing was sewn on the sock by hand. The hooks were then sewn on the cloth backings by hand. It was agreed, as discussed previously, for the gait analysis of Part IV, to add pressure sensors to the sock prototype to automate the gait cycle notation. A pocket was stitched at the bottom of the sock to attach these pressure sensors utilized in Part V [61] to the bottom of the foot, as shown in Figure 3.7 on page 34. In addition, the cables/wire handling problems were resolved by sewing a covering on the socks, through which
wires could be fed to the sensors to prevent tangling or bending. The pocket for pressure sensors, as well as the covers for wiring, was made of a cotton knit fabric.

Figure 3.6
Hook and eye attachment to hold SRS in place.

When developing the SSTK equipment, intentional design must be at the forefront of the process for ease of use and practicality. The challenge of creating a new enclosure that would be
Figure 3.7

Sock prototype featuring wire coverings and band to form-fit SRS.
both easy to disassemble and able to manage the excess wires without creating a potential hazard to the sensors presented itself. The computer-aided design (CAD) tool Autodesk Fusion 360™ was used to build a model of the sensor board, as seen in Figure 3.8. This sensor board model was used to form the enclosure’s basic framework.

![Figure 3.8](image)

**Figure 3.8**

Model board used to form a basic structure of the enclosure.

The cutouts were made for the wire connections, the power switch, and the snap buttons that would hold the enclosure on the sock. The edges of the enclosure were rounded for aesthetics and prevented the cable from rubbing against the edge of the box and potentially damaging the wire sheathing. A visualization of this portion is provided in Figure 3.9 on the following page.

Stand-offs were then developed to support the sensor in the enclosure to keep it from shifting during participant movement. One of the challenges presented by the enclosure configuration was
Figure 3.9

Cutouts for mounting and sensor accessibility.
a simpler way of accessing the sensor when working in the laboratory while performing the trials. Using screws on all four corners to secure two sides of the enclosure together would make the process of opening the enclosure and accessing the sensors more tedious. A snap case concept was used to make the method of opening and closing the enclosure less difficult and enable smoother and faster access to the sensors. This was accomplished by creating a 45° extrusion on one-half of the case and a matching divot on the other half, with the extrusion being smaller to ensure that there were no fitment issues. This allowed for easy disassembly with no external tools required. Figure 3.10 provides a visual for this design.

![Figure 3.10](image)

Snap case design for ease of access to the sensor.

The near-final case enclosure feature to mitigate all previous laboratory testing concerns was to develop a method for wire management. The wire management system was designed such that the wires could be wrapped or minimized depending on the necessary length needed for the participant. The wire management system, as shown in Figure 3.11 on the following page, used two alignment
holes and eight magnet slots to secure the cover. Pegs were used to align the cover with the holder, and an additional eight magnets were used to secure the cover to the holder. Lastly, all edges of the wire management system were smoothed using a fillet tool in the 3D design software to ensure no rough or sharp areas contacted the wires. Figure 3.11 features this casing in use along with its respective model design, while Figure 3.12 on the following page visualizes the differences in wire management between sock prototype iterations.

After lab testing, a few underlying issues with the design of the wire holder were identified. Being that each sensor has its own wire, the design of one large spool proved to be an issue as individual wires would become tangled when wrapping around a single spool. This overlapping would make the process of removing individual sensors nearly impossible, meaning that if one sensor were to be removed, all sensors would have to be removed from the sock. To combat this,
smaller spools were made for each of the six sensor wires such that each wire had its own spool to wrap around. Each spool utilized a single magnet at the top for securing the wire holder cover coupled with the attracting magnet to prevent the wires from unspooling. This new system is shown in Figure 3.13 on the next page.

In addition to the upgraded wire management system, a redesign of the sensor board resulted in a smaller iteration of the enclosure using similar methods to those shown in Figure 3.8 on page 35, Figure 3.9 on page 36 and Figure 3.10 on page 37. Figure 3.14 on the next page visualizes the new enclosure and wire management system placed on a gridded mat for scale reference.

This enclosure and wire management system will be the iteration taken in the laboratory for prototype validation, as static and dynamic movements from Closing the Wearable Gap papers Part II and Part IV are reassessed.
Figure 3.13

Updated wire management system.

Figure 3.14

Finalized wire management system on smaller board enclosures. (a) Top view of enclosure, (b) side view of enclosure, note opening on the side for the charging port.
3.4.5 Data Collection Graphical User Interface (GUI)

A software application was designed to communicate with the hardware module, record the stretch sensor data, and function as a tool for researchers and can be used during participant trials to view the data in real-time and review recorded data. This decision was made considering the relatively low and inconsistent sampling rate that occurred due to the off-the-shelf smartphone solution utilizing Bluetooth functionality. This new system was needed to support data collection from multiple modules simultaneously while being captured or sampled at a faster rate. The application was developed in Python 3 using the Qt5 library to create the GUI. This new GUI presents several features that will enable improvements in the data collection process for researchers as it assists with automating certain tasks, such as labeling trials. The new feature set from the GUI includes the ability for the experimenter to assign names to individual device channels, preventing the mislabeling of data series. Furthermore, collected data is plotted both during and after the recording event, allowing researchers to immediately verify the successful execution of the trial. Finally, its modular architecture and open-source license allow support for any remote data capture device to be integrated into the software. Figure 3.15 on the following page shows an example of the GUI being used to visualize the data collection in real-time.

3.5 Discussion of Limitations

To the knowledge of the researchers involved with this study, this research, where an SSTK was developed to aid SRS validation and wearable prototyping in a laboratory, is the first of its kind. As is documented in detail, several constraints were found during the series of investigative procedures and will be revisited.
GUI (graphical user interface) design, displaying data from ten SRS.

(a) The computing unit created for Closing the Wearable Gap Part I demonstrated minor noise levels, creating a variance in the electrical output at the time of data capture readings. The importance of a breadboard during the initial design stages was recognized but suggested quickly moving to a PCB design.

(b) The original wooden ankle model that was developed from an earlier model published in the literature [29] presented limitations. The rubber flooring material used to manipulate the wooden ankle joint for INV and EVR movements was problematic during the experiment. A considerable amount of force had to be applied to manipulate the model to certain joint angles, which was a data collection issue, as well as an ergonomic concern, affecting the wrists and hands of the researchers.
The use of a more flexible material that would be easier to move and manipulate for future model developments was suggested.

(c) Variance in participant’s gait patterns and stride lengths while walking on the flat surface and TSP created a lot of additional data cleaning. Gait research conducted by David Winter shows that every individual’s gait cycle is unique [91]. This variation in gait patterns made it more challenging to create prediction models that could generalize data well. Multivariable linear models began to be used to minimize the effect of coupled movements, influencing the outputs of the SRS as well as deep learning techniques to improve predictability. The new sock prototype discussed in Section 3.4.2 was developed as a reliable SRS mounting approach to maintain consistency between different SRS data collection sessions and to avoid possible pre-strain problems. Sock prototype Iteration III will ensure that SRS can be mounted on the sock fabric only in one manner. Therefore, the deep learning model can be successfully trained as there is experimental confidence that all participant data collection sessions for SRS measurements are repeatable and reliable. Furthermore, deep learning needs a vast amount of data to properly train a model. To collect more data to train the deep learning algorithms, conducting longer trials to collect a higher number of gait cycles will be essential.

(d) During the many initial linearity studies conducted, numerous sensors were broken at the contact point after completing several measurement cycles while testing them on the drill vise fixture. Berlin et al. indicated that the conductive fibers might have mechanical properties somewhat different from those of normal textile fibers, causing them to react differently to deformation, bending, and extension. Chemical effects should also be considered. Because of certain deformations, gradual yet steady fiber migration eventually causes the SRS to crack at the point of contact.
Thus, depending upon the fiber type and fabric structure, having a reliable contact point was found to be critically important. Further, excellent flexibility and stretchability are crucial components that can provide monitoring systems with the ability to continuously track the human body’s physiological signals without being invasive. For this, it was quickly found that it is necessary to consider the stretchability of the sensors based on the context of the area of research and the joint upon which the SRS is to be mounted. Most of the manufacturers provide a datasheet, indicating that the sensor can be stretched up to a certain proportion of its original length. Understanding the physical limitations of sensors became required learning for new members of the research team prior to experimentation.

(e) Resistance-based SRS was used for Closing the Wearable Gap Part I, whereas capacitance-based sensors have been used to-date for the remaining Closing the Wearable Gap paper studies. Before swapping from resistance-based SRS to capacitance-based SRS, several factors were considered. The electrical properties of the sensors under applied strain were a primary reason for the change in the SRS type. Hysteresis is important to consider when using the sensor in real-life applications as it results in an increase in a change in the output of the SRS at rest, making it more difficult to predict with a model [6]. An important lesson learned by the experimenters is the desire for consistent and common resting resistances, that is when the SRS is not stretched. While all the sensors were linear in their movement-to-stretch output, not all sensors had comparable resistance values at rest. When developing a reliable model, variability in the resting resistance is not preferred. In this case, there were sensors that were the same length but had various resting resistances. To overcome this issue, normalizing the data was suggested such that relative change is measured as opposed to absolute change. Nevertheless, the issue of resting resistance could still be
considered problematic when reproducibility and consistency of sensors are desired, as they make circuit design more challenging. Resistivity itself is often susceptible to different environmental factors, such as temperature and damage [37]. Due to the variance in resistance, a flexibly designed circuit was needed, which would add more complexity to the computing unit’s programming to determine the resting resistance for the sensors. Thus, an SRS having consistent resting resistance with known minimal hysteresis is preferred when capturing complex joint movements.

(f) Based on other literature in the field, resistive sensors possess strong sensitivity and excellent sensing efficiency. However, they suffer from poor long-term stability and linearity as well as substantial signal hysteresis. Alternatively, studies have suggested that capacitive sensors have better stability, lower hysteresis, and high stretchability [6, 37, 43, 31]. One of the other factors to be addressed during the preliminary analysis was whether a commercial-off-the-shelf (COTS) product existed that could already measure the SRS. Having a COTS sensor module that supports Bluetooth and connects to a smartphone companion application for real-time data collection can help save a great deal of time when carrying out preliminary studies. It is also important to note the number of sensors a module can record simultaneously when measurements of multiple movements are desired, as well as the supported sampling rate and whether that sampling rate is consistent. There are some companies that have fully developed software applications with various raw data streaming functionalities, while others give basic demonstrations.

3.6 Future Scope

Moving forward, a new iteration of experiments need to be performed to validate the most recent implementations of the hardware, sock prototype, and data analysis software. To collect a
dataset that is more suitable for deep learning analysis, a new gait study will be conducted where participants will walk on a treadmill, while SRS and motion capture data are collected for longer periods of time. This will strengthen the accuracy of the deep learning models as there will be a stronger presence of patterns in the data for the models to analyze. This will also help determine the efficacy of the most recent sock prototype. Additionally, the sock prototype will be evaluated while shoes are worn to investigate how the models are affected during gait.

Finally, as the mounting method for sensors on the ankle becomes finalized, further research can be done using stretch sensors on other parts of the body while undergoing other human activities. One of the next steps for this would include using stretch sensors to model kinematics at the knee joint while a participant is riding a stationary bicycle. Other activities will include collecting data outside of the laboratory environment in athletic settings, such as basketball. In terms of conducting research with other types of SRS, future work will need to be done to create a module that is sensor-agnostic with a daughter board designed for each type of SRS (based on electrical properties and connection-type) that will connect to a primary data collection module.

### 3.7 Conclusions

The NSF I-Corps training process has taught the Athlete Engineering research team the criticality of capturing requirements from the end-user practitioner, which, in this case, is the S&C coach, athletic trainer, or any other practitioner charged with making health and safety decisions that keep all athlete types protected during improvement-based training. During a series of interviews, S&C coaches have explained the importance of having technology solutions that exist outside of the laboratory while being equally as trustworthy and effective in their data collection. IMU-based
wearables close this gap somewhat, but, due to their drift and other inconsistency issues, SRS provides an option that may further “Close the Wearable Gap”, as has been presented in the ongoing paper series. To utilize SRS, another gap has to be closed, and that is the creation of SSTK solutions that would provide repeatability and reliability to the testing and validation of SRS. The research team has gained a great amount of knowledge regarding SRS and how to best evaluate their ability to model kinematic data. Several testing apparatuses have been constructed as part of the SSTK to validate the SRS against direct stretch and stretch-related movements to simulated and actual foot movements. A suite of analysis scripts has been developed in R and MATLAB to preprocess and analyze SRS and motion capture data by means of linear and multi-linear regression as well as deep learning techniques. Further, several iterations of a sock prototype have been constructed, where the methods for mounting SRS to socks for participant trials gradually improved. Research will continue towards conducting a new series of experiments, utilizing a new hardware prototype, software GUI, and sock mounting technique, to collect more robust datasets for further validation and progression of SRS design in modeling human kinetic and kinematic data.
CHAPTER 4
PROTOTYPE AND METHODOLOGY VALIDATION

4.1 Introduction

Human motion capture and analysis is typically performed using an expensive system of digital cameras and reflective markers in a laboratory setting. More recently, low-cost wearable electronic sensors have worked toward moving motion analysis out of the lab and into the field [73]. Commonly, this has been accomplished using networks of inertial sensors and gyroscopes; unfortunately, these kinds of sensors suffer from several problems related to accuracy and accumulation of errors (IMU drift) [73]. This research follows in a series of academic works titled "Closing the Wearable Gap" aiming to improve portable motion capture technology using soft robotic sensors (SRSs). A wearable system capable of capturing human ankle motion in the form of a sock has been iteratively developed and modified. The primary goal of this developing this prototype is to build a portable system "from the ground up" that can estimate ankle joint angles within a reasonable degree of accuracy to facilitate higher-level analyses of gait, athletics, and beyond.

4.1.1 Biomechanical Analysis

Before extending movement analyses to high-level activities such as gait or jumping, a system must be developed that can accurately and reliably estimate joint angles over time. The human ankle joint can be modeled with two planar angles: sagittal (Figure 4.1 on the next page) and frontal
Within these two planes, four basic movements can be made: plantarflexion (PFX), dorsiflexion (DFX), inversion (INV), and eversion (EVR) [28]. Plantarflexion and dorsiflexion represent upward (positive angle) and downward (negative angle) movements along the sagittal plane, while inversion and eversion represent inward (positive angle) and outward (negative angle) movements along the frontal plane [28]. This research continues development toward a stretch sensor-based wearable device that can accurately record and estimate these movements.

Figure 4.1

Sagittal plane: (a) neutral; (b) dorsiflexion; and (c) plantar flexion. (adapted from [78])
Figure 4.2

Frontal plane: (a) neutral; (b) inversion; and (c) eversion. (adapted from [78])
Gait analysis plays an important role in the field of rehabilitation and injury prevention for athletic populations and the general public. To evaluate the gait cycle, the Rancho Los Amigos (RLA) gait analysis committee generated a generic terminology for the different phases of the gait cycle [75]. Analyzing gait cycles by phases directly identifies the functional implication of different movements produced at specific joints [70]. A healthy gait cycle is categorized into two main phases, stance and swing [70]. One complete gait cycle includes both a stance and swing phase [70]. Throughout the stance phase, the foot is in contact with the ground for 60% of the gait cycle [70]. While in the swing phase, that same foot is no longer in contact with the ground and is swinging over in preparation for the following foot strike [70]. The swing phase accounts for 40% of the gait cycle [70]. These two main phases can be further subdivided into eight distinct subphases - initial contact, loading response, mid-stance, terminal stance, pre-swing, initial swing, mid-swing, and terminal swing [70].

4.1.2 Progress and Improvements

In Closing the Wearable Gap: Part II [78] and Closing the Wearable Gap: Part IV [77], a proof-of-concept prototype was developed to determine the viability of using soft robotic sensors (SRSs) for measuring joint angles in the human foot-ankle complex. Following the promising results of these studies, the prototype device has undergone many changes and improvements toward developing a more durable and reliable lab tool (Figure 4.3 on the next page). These improvements are designed to address a number of challenges and limitations of the previous version of the prototype. Many of these changes are detailed in 3.4; major improvements will be summarized in this section.
Figure 4.3

Sock prototype from the previous studies (left) and current one (right).
4.1.2.1 Sock Garment Prototype

Early prototypes used Velcro™ mounts for the SRSs and used athletic straps to attach the electronics enclosure to participants. Problems with this model included damage to the sock by the Velcro™, decreasing the sock’s lifespan. The newer models attach the SRS with hook and eye closures and mount the electronics enclosure using button snaps. These hooks are less likely to cause damage to the sock and are sewn to the sock in a way that allows the fabric to stretch with the body as if nothing was on the sock. The Velcro™ of earlier models was glued on, causing the sock to be rigid in those areas.

Further upgrades to the sock included the addition of a pressure sensor pocket under the heel that facilitates synchronization with a camera-based motion capture system, and fabric coverings which protect the wires of the sensors when the sock is being put on and taken off. Both the pocket and covering were made with cotton jersey fabric which allows the sock to stretch naturally.

4.1.2.2 Electronics and Cable Management

The latest iteration of the 3D printed electronics enclosure was used to house the data collection device and mount the device to the sock. The enclosure features viewing ports for led indicators, a charging port, and power switch, allowing for quick access to the device without having to take the enclosure apart.

Wire management for the prototype is handled using small spools with magnetic caps attached to the enclosure. These spools are responsible for housing and protecting any excess sensor cable. The cables wrap around the spools and are secured with a magnetic cap. The cap sits flush with
the case aside from two small cutouts for only an inlet and outlet preventing any cables unravelling during data collection.

The sensing electronics within the enclosure handle sensor measurement, power management, and Bluetooth communication. Using an Espressif (Shanghai, China) ESP32 system-on-a-chip (SoC) and a StretchSense™ 10-channel SPI sensing board (Auckland, New Zealand), the electronics board reads sensor values and transmits them to a remote PC via a custom Bluetooth protocol. Because the device contains several off-the-shelf components which need to be electrically and mechanically bonded, a printed circuit board (PCB) backplane was developed to make these connections. Use of a PCB helped shrink the overall device size, weight, and assembly time.

More information about this enclosure and contained electronics can be found in section 3.

4.1.3 Contributions

The contributions of this work include:

• Presentation of an improved hardware prototype from Closing the Wearable Gap: Part II and Part IV [78, 77].

• Validation of measurements captured by the new prototype and comparison to camera-based motion capture.

• Statistical significance tests showing equivalence or improvement in the new prototype compared to the previous versions.

• Results show that the wearing of shoes with the sock prototype does not negatively affect its performance.

4.2 Materials and Methods

This research uses the same methods of validation as parts II and IV of the "Closing the Wearable Gap" publication series [78, 77] so that the prototype being validated in this work can
be compared directly to the prototype discussed in those papers. Because of these similarities and nearly identical experimental procedures, some of the wording and structure of this work may originate from those papers. Any changes herein exist to describe improvements made to hardware or processes or differences in participant population.

4.2.1 Participants

Ten (10) participants (five males: age, 21-24; height, 170cm-195cm; mass, 72kg-112kg; foot size, 9.5-13 (US); and five females: age, 19-23; height, 168cm-175cm; mass, 58kg-78kg; foot size, 7.5-10.5 (US)) with no self-reported recent history of lower extremity musculoskeletal injuries or surgeries were tested. This number is consistent with prior validation studies for motion measurement prototypes such as this one [78, 77] and other recent wearable validation studies [66, 38, 41]. The study was approved for human subjects testing under the University’s Institutional Review Board (IRB protocol #17-725). Informed consent was obtained for all participants after fully explaining the protocol along with the risks and benefit involved.

4.2.2 Study Design

For this study, participants were instructed to visit the Human Performance Lab (HPL) at Mississippi State University’s (MSU) Center for Advanced Vehicular Systems (CAVS). Each participant arrived only a single day and was familiarized with the study protocol and its goals before participating. Once familiar with the study, the participant put on both sock prototypes and was fitted with motion capture clusters. The study consisted of two parts, each performed with and without the participant wearing shoes. The first part asked that the participant perform four ankle motions while sitting on a stool with their foot elevated while the stretch sensor and motion capture
data were recorded. These motions were plantarflexion, dorsiflexion, inversion, and eversion. In the second part, the participant was asked to walk across the room six times while the stretch sensor and motion capture data were recorded.

4.2.3 Instrumentation and Participant Preparation

The experimental testing included measurements of ankle joint kinematics using 12 Bonita 10 cameras functioning as a 3D motion capture system (Vicon, Oxford, UK). The SRSs (eight stretch sensors, two pressure sensors) used in the sock prototype were produced by StretchSense™ (Auckland, New Zealand). Both the motion capture system and stretch sensor measurement electronics were set to record at 125 Hz. Before data collection, each participant was calibrated into the motion capture system with four retro-reflective marker clusters and donned both sock prototypes. The marker clusters were fixed to both the left and right shanks and feet so that both axes of rotation about the ankle could be recorded.

4.2.4 Experimental Procedures

Participants were asked to read and fill out an informed consent form if they agreed per IRB protocol. Next, the participant was directed to a chair and given sock liners and the sock prototypes. Participants were directed verbally through the process of donning the sock without breaking any components; the socks were then visually inspected for any disconnected sensors or folds in the sock which could cause issues. Next, the participant would have the four marker clusters attached to their left and right knee shanks and feet, and the motion capture system would be calibrated to the locations of the sensors. A quick system test was performed to visually verify correct function of the stretch sensors and motion capture system. Then, the participant was asked to sit on a stool
as shown in Figure 4.4. They were then instructed to perform each of the same four movements performed in the Part II study [78]: plantarflexion, dorsiflexion, inversion, and eversion. After successfully recording each of the four movements, the participant was asked to stand in one corner of the motion capture space and walk across the room to the other corner, start with their right foot. These gait sessions were recorded and repeated six times.

Figure 4.4

A participant wearing the sock prototype during a static movement trial.
After completing each of these recordings, the motion capture clusters were removed, and the participant was asked to put on shoes of an appropriate size provided by the lab (Figure 4.5). A sock liner was worn between the shoe and sock to prevent the hook and eye closures from snagging the shoe and to help keep the shoe clean. Motion capture clusters were reattached and the system recalibrated. Finally, the data collection steps described in the previous paragraph were repeated with the participant wearing the shoes.

Figure 4.5

A participant wearing shoes over the sock prototype.
4.2.5 Data Preprocessing

All data preprocessing and analysis steps were implemented using the Python (3.8.5) [1] programming language and open-source packages such as pandas (1.1.4) for data manipulation and structuring [69], SciPy (1.5.3) for scientific functions and filters [81], and matplotlib for generating plots (3.3.2) [64].

The first step in processing each trial is to trim and time-align the StretchSense™ and motion capture data. Because the motion capture system and each Bluetooth communication module may have slightly differing time values, cross correlation must be used to align the signals. First, the motion capture and stretch sensor values for each trial were read from their respective files. Then each signal was low-pass filtered using a 3rd order Savitzky-Golay filter with a window length of 51. This aggressive filtering is acceptable for time-alignment as having smoother, less noisy data can improve the cross-correlation result. Next, an intermediary alignment series is calculated by subtracting the plantarflexion (PFX) measurements from the dorsiflexion (DFX) measurements and the eversion (EVR) measurements from the inversion (INV) measurements. The resulting time-series more closely resembles its respective motion capture time-series than either sensor measurement alone. The cross correlation function is used to calculate an optimal lag and a score at that lag between the two signals. Lags for both the flexion (FLX) and inversion-eversion (IEV) series are calculated for each trial, and the lag with the better score is chosen between the two. Visual inspection of plots (ex. Figure 4.6 on the following page) was used to verify that a reasonable lag was selected for each data series. The lag was then applied to the original (unfiltered) data and exported to a single file.
This preprocessing method was applied to all trials, static and dynamic. After preprocessing, the two types of trials were analyzed for prediction accuracy differently.

4.2.5.1 Static Movement Trials

Static movement trials were processed by first dropping any timesteps for which no data was present in any one data series. This has the effect of trimming off the beginning and end of each
trial’s data in the regions where one capture system had started or stopped before the other. Then, each data series was low-pass filtered using a 3rd order Savitzky-Golay filter with a window length of 15; this has an effective cutoff frequency of 15 Hz [80]. Next, a linear model for predicting the appropriate angle for its movement was fit to the data. The model was configured to predict the FLX angle for PFX and DFX movement trials and the IEV angle for INV and EVR movement trials. The coefficient of determination ($R^2$) and root-mean-squared error (RMSE) were calculated and saved for statistical analysis.

Finally, this procedure was repeated for all trials, but with all four sensor values being used to predict the movement angle by a linear model. The resulting scores were also saved for later analysis.

4.2.5.2 Dynamic Movement Trials

Dynamic movement trials were processed by trimming the data to include only full gait cycles captured by the recording then using a 3rd order Savitzky-Golay filter to remove any frequency content above 7.0 Hz as was done in Part IV [77] [80]. Then, a multi-variable linear model was used to fit each joint angle using all four sensor values. The same scoring metrics as the static trials were used with the addition of mean absolute error (MAE). The score values were saved for later analysis.

4.2.6 Statistical Analysis

Finally, the results for both static and dynamic trials were compared to the appropriate results of the Part II and Part IV studies, respectively, to check for any statistically significant changes in measurement accuracy. Additionally, the results of using a single variable and multi-variable model
for the static movements were compared. In both the static and dynamic analyses, a significance test between barefoot and shoed trial scores was also evaluated. In all cases, the selected mean accuracy scores ($R^2$, RMSE, MAE) across each category were used for the comparison. The significance test used was Welch’s t-test, a generalization of the Student’s t-test for samples of potentially unequal variance [90]. Welch’s t-test was used because one of the goals of improving the sock prototype was to improve measurement repeatability and reduce variance in accuracy scores. Thus, identical variance between sample populations could not be assumed. Results assumed to be significant were those with $p$-values less than 0.05; this is consistent with similar literature [41, 7, 85].

4.3 Results

Validation of the Part VIII prototype is divided into two phases: static movements and dynamic movements. In the static movements section (4.3.1), the prototype and analysis results scores are compared to those collected using the sock prototype in Closing the Wearable Gap: Part II [78]. In the dynamic movements section (4.3.2), the prototype and analysis results scores are compared to those collected using the sock prototype in Closing the Wearable Gap: Part IV [77]. In either case, the goal is to show that the Part VIII prototype yields statistically equivalent or better results than the Part II prototype in all cases.

4.3.1 Static Movements

The results of the analyses for each trial are presented in subsequent sections. Two metrics are used to evaluate the performance of the model: the coefficient of determination ($R^2$) and root-mean-square error (RMSE). $R^2$ is a common calculation which uses the variance of two variables
to score the effectiveness of a statistical model. RMSE is often used in technical and engineering settings to evaluate the effectiveness of an estimator; it is very sensitive to large, transient errors.

Some trials’ correlation scores were far outside of similar trials’ scores. Upon investigation, it was discovered that these poor results were caused by invalid tracking from the motion capture system; values were reported which were physically impossible for the human ankle without sustaining serious injury. As a result, these trials were excluded from the results and are marked with a “-” in the results tables.

4.3.1.1 Single-Sensor Linear Model

The results for each trial using single-variable linear modelling to predict the appropriate joint angle for each sensor are presented in Table 4.1 on the next page. For plantarflexion (PFX) and dorsiflexion (DFX) movement trials, the output is predicting flexion (FLX) angle. For inversion (INV) and eversion (EVR) movement trials, the output is predicting inversion-eversion (IEV) angle. Scores are shown for each movement trial by participant, movement, and configuration (barefoot/shoed) and as averages for each group.

4.3.1.2 Comparison to Previous Prototype Results

Table 4.2 on page 65 shows overall mean scores from the prototype validated in Closing the Wearable Gap: Part II [78] and overall mean scores from Table 4.1 on the next page. The scores from the best placement positions from [78] were used. Two-tailed significance test results between the two datasets are shown at the bottom of the table; significant results \( p < 0.05 \) are shown in **bold text**. Table 4.2 on page 65 shows that in all cases the Part VIII prototype performed statistically equivalently or better than the Part II prototype.
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<th>Barefoot</th>
<th>Shoe</th>
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**Mean**

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<td>2.47</td>
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Table 4.2

Statistical comparison between previous prototype (Part II) and current prototype (Part VIII) performance using coefficient of determination ($R^2$) and root-mean-squared error (RMSE).

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<td>0.976</td>
<td>0.953</td>
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<td>0.018</td>
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<td>1.99</td>
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<td>0.039</td>
<td>0.052</td>
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<td>1.56</td>
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<td>0.65</td>
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<td>($p$-value)</td>
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<td>0.458</td>
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4.3.1.3 Comparison between Barefoot and Shoed Trials

The results shown in Table 4.3 on the next page compare trials in which the participant was not wearing shoes over the sock prototype, or "barefoot," to trials in which a shoe was worn. The two-tailed significance test results show that in no cases did the presence of shoes cause significant degradation of motion measurements.

4.3.1.4 Comparison to Multi-Sensor Linear Model

In Table 4.4 on page 67, prediction scores for planar joint angles using a multi-variable linear model are shown. In these analyses, all four sensor measurements are used to predict joint angles in an effort to decouple sensor measurements with multiple angular components. Table 4.5 on page 68 shows mean scores of both barefoot and shoed trials comparing the use of a single linear model to a multi-variable linear model. A two-tailed significance test was run to compare the two
Table 4.3

Statistical comparison between barefoot and shoed trial scores using coefficient of determination (R²) and root-mean-squared error (RMSE).

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<td>Mean</td>
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<td>0.974</td>
<td>0.963</td>
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<tr>
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<td><strong>Shoed</strong></td>
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<td></td>
<td></td>
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<td>Mean</td>
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<td>0.961</td>
<td>0.959</td>
<td><strong>0.960</strong></td>
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<tr>
<td>SD</td>
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<td>1.96</td>
<td>1.91</td>
<td>2.24</td>
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<tr>
<td>(p-value)</td>
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<td>0.954</td>
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<td>0.318</td>
<td>0.686</td>
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</table>

models; significant findings (p < 0.05) are shown in **bold text**. Significant results occurred for plantarflexion and eversion movements.

4.3.2 Dynamic Movements

Table 4.6 on page 69 presents mean estimation scores for walking trials for each participant. For each score, a multi-variable linear model was used to predict either flexion or inversion-eversion angle using all four sensor values. As discussed in Closing the Wearable Gap: Part IV [77], mean absolute error (MAE) is used as a metric for these trials so that significant weight is not added to large, transient errors. MAE can be interpreted similarly to RMSE; lower numbers are better and represent an average error in degrees to the ground truth.
Table 4.4

Angle estimation scores in coefficient of determination (R$^2$) and root-mean-squared error (RMSE) by trial using a multi-variable linear model.

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<td>0.988</td>
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<td>0.987</td>
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<td>0.995</td>
<td>-</td>
<td>0.979</td>
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<td>0.995</td>
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Table 4.5

Statistical comparison between Single Linear Model (SLM) and Multiple Linear Model (MLM) scores using coefficient of determination ($R^2$) and root-mean-squared error (RMSE).

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<th>EVR</th>
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<td>0.962</td>
<td>0.966</td>
</tr>
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<td>0.987</td>
<td>0.987</td>
</tr>
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<td>1.41</td>
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<td>0.003</td>
<td>0.027</td>
<td>0.014</td>
<td>0.009</td>
<td>0.013</td>
</tr>
<tr>
<td>RMSE (°)</td>
<td>0.49</td>
<td>1.02</td>
<td>0.52</td>
<td>0.50</td>
<td>0.63</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Significance Test</th>
<th>R²</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(p-value)</td>
<td></td>
<td>0.018</td>
<td>0.420</td>
<td>0.176</td>
<td>0.005</td>
</tr>
<tr>
<td>RMSE (°)</td>
<td></td>
<td>0.007</td>
<td>0.339</td>
<td>0.109</td>
<td>0.006</td>
</tr>
</tbody>
</table>

4.3.2.1 Comparison to Previous Prototype

The results of a two-tailed significance test comparing the Part IV prototype to the Part VIII prototype are shown in Table 4.7 on page 70. Results show that using the average scores from all trials, there was no significant decrease in performance by any metric from the Part IV prototype. Notably, mean variance across scores is lower than those presented in the Part IV paper [77].

4.3.2.2 Barefoot vs. Shoe Comparison

Table 4.8 on page 70 shows the results of a statistical significance comparison between the barefoot and shoed trials mean scores. The $p$-value results show that no significant performance degradation occurs when the participant is wearing shoes. While the $R^2$ value is slightly lower for the shoed trials, RMSE and MAE values decreased, further supporting the non-effect of wearing shoes on the prototype’s performance.
Table 4.6

Angle estimation scores in coefficient of determination ($R^2$), root-mean-squared error (RMSE), and mean absolute error (MAE) for dynamic trials using a multi-variable linear model.

<table>
<thead>
<tr>
<th></th>
<th>Barefoot Adj. R²</th>
<th>RMSE (°)</th>
<th>MAE (°)</th>
<th>Shoed Adj. R²</th>
<th>RMSE (°)</th>
<th>MAE (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P001</td>
<td>Mean</td>
<td>0.808</td>
<td>2.21</td>
<td>1.70</td>
<td>Mean</td>
<td>0.771</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.054</td>
<td>0.19</td>
<td>0.12</td>
<td>SD</td>
<td>0.040</td>
</tr>
<tr>
<td>P002</td>
<td>Mean</td>
<td>0.934</td>
<td>1.82</td>
<td>1.44</td>
<td>Mean</td>
<td>0.924</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.012</td>
<td>0.17</td>
<td>0.11</td>
<td>SD</td>
<td>0.023</td>
</tr>
<tr>
<td>P003</td>
<td>Mean</td>
<td>0.910</td>
<td>2.09</td>
<td>1.67</td>
<td>Mean</td>
<td>0.915</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.021</td>
<td>0.16</td>
<td>0.11</td>
<td>SD</td>
<td>0.016</td>
</tr>
<tr>
<td>P004</td>
<td>Mean</td>
<td>0.792</td>
<td>2.24</td>
<td>1.80</td>
<td>Mean</td>
<td>0.821</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.034</td>
<td>0.25</td>
<td>0.16</td>
<td>SD</td>
<td>0.025</td>
</tr>
<tr>
<td>P005</td>
<td>Mean</td>
<td>0.802</td>
<td>2.28</td>
<td>1.70</td>
<td>Mean</td>
<td>0.827</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.101</td>
<td>0.64</td>
<td>0.32</td>
<td>SD</td>
<td>0.040</td>
</tr>
<tr>
<td>P006</td>
<td>Mean</td>
<td>0.812</td>
<td>3.81</td>
<td>2.98</td>
<td>Mean</td>
<td>0.730</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.091</td>
<td>2.81</td>
<td>2.25</td>
<td>SD</td>
<td>0.062</td>
</tr>
<tr>
<td>P007</td>
<td>Mean</td>
<td>0.764</td>
<td>2.43</td>
<td>1.98</td>
<td>Mean</td>
<td>0.662</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.040</td>
<td>0.09</td>
<td>0.08</td>
<td>SD</td>
<td>0.072</td>
</tr>
<tr>
<td>P008</td>
<td>Mean</td>
<td>0.692</td>
<td>2.62</td>
<td>2.15</td>
<td>Mean</td>
<td>0.766</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.057</td>
<td>0.29</td>
<td>0.28</td>
<td>SD</td>
<td>0.050</td>
</tr>
<tr>
<td>P009</td>
<td>Mean</td>
<td>0.793</td>
<td>1.74</td>
<td>1.38</td>
<td>Mean</td>
<td>0.709</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.024</td>
<td>0.16</td>
<td>0.12</td>
<td>SD</td>
<td>0.050</td>
</tr>
<tr>
<td>P010</td>
<td>Mean</td>
<td>0.818</td>
<td>2.35</td>
<td>1.81</td>
<td>Mean</td>
<td>0.886</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.023</td>
<td>0.17</td>
<td>0.10</td>
<td>SD</td>
<td>0.042</td>
</tr>
<tr>
<td>Overall</td>
<td>Mean</td>
<td>0.813</td>
<td>2.36</td>
<td>1.86</td>
<td>Mean</td>
<td>0.801</td>
</tr>
<tr>
<td></td>
<td>SD</td>
<td>0.068</td>
<td>0.57</td>
<td>0.45</td>
<td>SD</td>
<td>0.089</td>
</tr>
</tbody>
</table>
Table 4.7

Statistical comparison between Part IV prototype performance and Part VIII prototype performance using coefficient of determination ($R^2$), root-mean-squared error (RMSE), and mean absolute error (MAE).

<table>
<thead>
<tr>
<th></th>
<th>Part IV</th>
<th>Part VIII</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.854</td>
<td>0.812</td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>1.96</td>
<td>2.36</td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>1.54</td>
<td>1.86</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.134</td>
<td>0.069</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>0.78</td>
<td>0.57</td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>0.61</td>
<td>0.45</td>
</tr>
<tr>
<td><strong>Significance Test</strong></td>
<td><strong>p-value</strong></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.390</td>
<td></td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>0.362</td>
<td></td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>0.154</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.8

Statistical comparison between Barefoot and Shoed dynamic walking trials using coefficient of determination ($R^2$), root-mean-squared error (RMSE), and mean absolute error (MAE).

<table>
<thead>
<tr>
<th></th>
<th>Barefoot</th>
<th>Shoed</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.812</td>
<td>0.801</td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>2.36</td>
<td>2.13</td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>1.86</td>
<td>1.69</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.069</td>
<td>0.089</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>0.57</td>
<td>0.52</td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>0.45</td>
<td>0.40</td>
</tr>
<tr>
<td><strong>Significance Test</strong></td>
<td><strong>p-value</strong></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.761</td>
<td></td>
</tr>
<tr>
<td>RMSE ($^\circ$)</td>
<td>0.373</td>
<td></td>
</tr>
<tr>
<td>MAE ($^\circ$)</td>
<td>0.384</td>
<td></td>
</tr>
</tbody>
</table>
4.4 Discussion

Parts II and IV of the "closing the wearable gap" paper series explored the usage of SRSs for capturing both simple foot movements and gait [78, 77]. The prior research showed that joint angle estimation using stretch sensor measurements with approximately $2^\circ$ accuracy is feasible. In this research, a prototype adhering to the basic design principles of the original with modifications improving ease of use and durability was tested in the same way. By comparing these two prototype revisions using the same experimental process and error metrics, performance degradation, if any exists, can be detected and evaluated.

4.4.1 Static Movements

The first goal in studying the static movement trials was to determine if the current prototype revision could match the performance of the previous revision. To do this, a two-tailed significance test was run on each pair of corresponding scores from the prototype used in Part II of the paper series and the current study (Table 4.2 on page 65). A non-significant ($p > 0.05$) finding indicates that the two prototypes are matched in performance within a reasonable margin error. One of these significance tests, however, did indicate significant result; the mean RMSE for eversion (EVR) trials equaled 0.004. In this case, the current prototype had significantly outperformed the Part II prototype by a significant value. Thus, the first goal of validating the current prototype against the previous prototype was successful.

Secondly, a goal of this research was to measure the effect, if any, that wearing shoes over the sock prototype had on its performance. Again, a two-tailed significance test was run on the mean scores against barefoot trials and shoed trials (Table 4.3 on page 66). No significant differences
were indicated on any pair, with the minimum $p$-value being 0.122 for the mean $R^2$ on plantarflexion (PFX) trials. Thus, the key result of this comparison is that wearing shoes over the sock prototype causes no significant degradation in measurement quality.

Finally, both single sensor and multi-sensor linear prediction models were fit to the data and their accuracy scores compared. The goal of this was to give an idea of both how much coupling between sensors and multiple movements exists and how much the opposite sensors overlap in range of motion. A two-tailed significance test was run on the corresponding mean scores between each model type (Table 4.5 on page 68). The results showed that significant improvement using the multi-sensor model occurred for plantarflexion (PFX) and eversion (EVR) trials. Two contributing explanations for this are that: (a) because of the angle at which each sensor is attached, the PFX and EVR sensors are the most prone to movement coupling and (b) the plantarflexion and eversion movements are the most difficult for participants to isolate — i.e., eversion is a difficult movement to exert without also performing some plantarflexion (and vice versa). The data seems to show that some sensor-movement coupling is inevitable and a multi-sensor model will provide better results in many cases.

4.4.2 Dynamic Movements

In the same way that the previous prototype and current prototype were compared using the static movement trials, the dynamic movement trial analysis results from the Part IV prototype were compared to the results using the current prototype. A two-tailed significance test was run between the two datasets (Table 4.7 on page 70). The results showed no significant ($p < 0.05$) degradation in performance between the two prototypes; the minimum $p$-value found in all comparisons was
0.154. Notably, in both the Part IV results and the current results, the goodness of fit is lower than that of the static movements. This is probably due to the non-linearity of some coupled movement effects; this will be further discussed in section 4.4.3.

Again, a two-tailed significance test was run to compare the barefoot vs. shoed trials for dynamic movements. Similarly to the static movement results, no significant \( (p < 0.05) \) difference was found in the accuracy scores. This shows that for complex movements such as walking, wearing shoes over the sock prototype makes no significant difference.

4.4.3 Limitations

Though the results of this data collection and analysis were largely consistent and repeatable, a couple of limitations exist which may need to be addressed in the future.

4.4.3.1 Excluded Trials and System Malfunctions

As noted in section 4.3.1, some static movement trials suffered from various system malfunctions and were excluded from the analysis. The first of these error types is related to the motion capture system; sometimes, the system loses track of one or more marker clusters and records inaccurate measurements. An example of this is shown in Figure 4.7 on the next page. Unfortunately, this is one disadvantage to camera-based motion capture in general; obscuring of cameras in some activities can be unavoidable. One of the advantages of a stretch sensor based motion capture system is that movements can be captured in scenarios where camera-based motion capture is impractical such as in sports games, tight or crowded spaces, and outdoors.
Figure 4.7

An example of motion capture (blue) losing sync with the true position of the participant’s foot.
4.4.4 Future Work

Future work includes finding ways to overcome some of the aforementioned limitations of the system. Researchers would greatly benefit from increasing the battery life of the prototype by including a higher capacity battery or by implementing a system by which the battery can be quickly replaced and recharged offline. Additionally, some method of decreasing friction between the stretch sensors and any surfaces it may rub against may be worth researching to improve accuracy.

Next steps for data analysis include using the sensor data to extract higher-level information such as gait characteristics or walking abnormalities. Such method would most likely be implemented by collecting more data so that deep learning techniques can be employed.

4.5 Conclusions

Goodness of fit scores such as $R^2$, RMSE, and MAE were used to compare an updated prototype to its previous version. Camera-based motion capture and stretch sensor recordings were collected using the same type of movements as parts II and IV of the “closing the wearable gap” paper series. A series of Welch’s $t$-test calculations and statistical significance comparisons were used to determine if any performance metrics were significantly different than the previous prototype version. Additionally, all movements were repeated with the participants wearing shoes so that the effects of wearing shoes could be studied as suggested in Part II [78].

Findings showed no significant performance degradation between the previous prototype and the current prototype for either static or dynamic movements. Also, the use of shoes did not significantly affect the prototype’s performance. In the Part II study and the static movement
analysis for this research, a linear model was used for estimating a joint angle of interest using a single sensor. The results show that even for simple movements, a multi-sensor model yields better results due to coupling of multiple movements to each sensor.
CHAPTER 5

CONCLUSIONS AND FUTURE WORK

Using the work presented in Parts II and IV of the "Closing the Wearable Gap" series [78, 77] as a launchpad, I was able to validate a vast series of improvements to an initial prototype without significantly \((p < 0.05)\) sacrificing performance exhibited by the previous prototype. I conducted a study involving ten participants wherein this validation against the previous prototype was carried out; additionally, I validated the correct function of the prototype in conjunction with shoes. In all cases, the stretch sensor-based prototype outputs were scored against the outputs of a camera-based motion capture system. These scores were then statistically compared based on the test conditions for each group of scores. The end result is a more durable, user-friendly, and manufacturable hardware sock prototype which is at least as performant as the initial prototype.

5.1 Future Work

Despite the progress made in this research effort, a great amount of work is ahead still for the development of the prototype. The particular sensor design used in the prototype has been discontinued, thus a suitable replacement will need to be integrated into the prototype. As SRSs continue to lower in price and the prototype design becomes more durable, the SRSs will need to become permanently integrated into the sock prototype. Finally, some features of the prototype
are not capable of being manufactured automatically; these will eventually need to be reworked so that automatic machines could produce the product.

Future experiments continuing on the path of extracting useful information from the prototype data include collection of a large dataset, allowing deep learning techniques to be used on the data. Additionally, more studies like this one may need to be performed as the prototype design continues to evolve and new sensor designs are integrated.
REFERENCES


