Golf Glove Data-based Swing Classification through Machine Learning

By

Jackson D. Fletcher

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Name: Jackson D. Fletcher

Date of Degree: May 4, 2019

Institution: Mississippi State University

Major Field: Computer Engineering

Major Professor: John E. Ball

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Candidate for Degree of Cursus Honorum

A golf swing is biomechanically complex. Professional swing training is expensive for the average golfer. With the growing development of small inertial sensors and powerful microprocessors with built-in wireless communication protocol support, embedded devices are becoming suitable for tough tasks like motion tracking. The proposed solution consists of a sensor-packed golf glove. To evaluate the efficacy of the proposed solution, a recurrent neural network is developed that uses a learning model to identify golf swings that produce a slice, the most common golf swing error. A motion capture system was used as the professional baseline for the evaluation. Barely falling short of the professional solution's performance, the proposed solution showed potential to become a portable and economical alternative.

DEDICATION

To my parents.

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g Constant representing the gravitational force on Earth

IMU Inertial measurement unit

LSTM Long short-term memory

NN Neural network

RNN Recurrent neural network

CHAPTER 1

INTRODUCTION

1.1 Motivation

Golf is challenging. The one mechanical motion involved in golf—the golf swing—is biomechanically complex. By extension, it is tough to master, and most amateur golfers struggle to consistently hit the ball straight.

Golf swing training tools currently on the market are prohibitively expensive to the average consumer. Additionally, professional instruction is temporary and professional training systems are bulky, and restricted to laboratories.

The proposed glove system, seen in Figure 1.1, intends to remove these long-standing barriers to a better swing. At the core of the glove's sensor arsenal are two inertial measurement units (IMU) which measure linear acceleration and rotational velocity. The glove also integrates flexible sensors that measure important biomechanical information like wrist flexion, extension, and grip pressure.

1.2 Objective

To characterize the proposed solution's viability as an alternative to professional training devices, this study will evaluate its motion tracking capabilities. Specifically, the collected motion data will be analyzed via machine learning to determine if it can

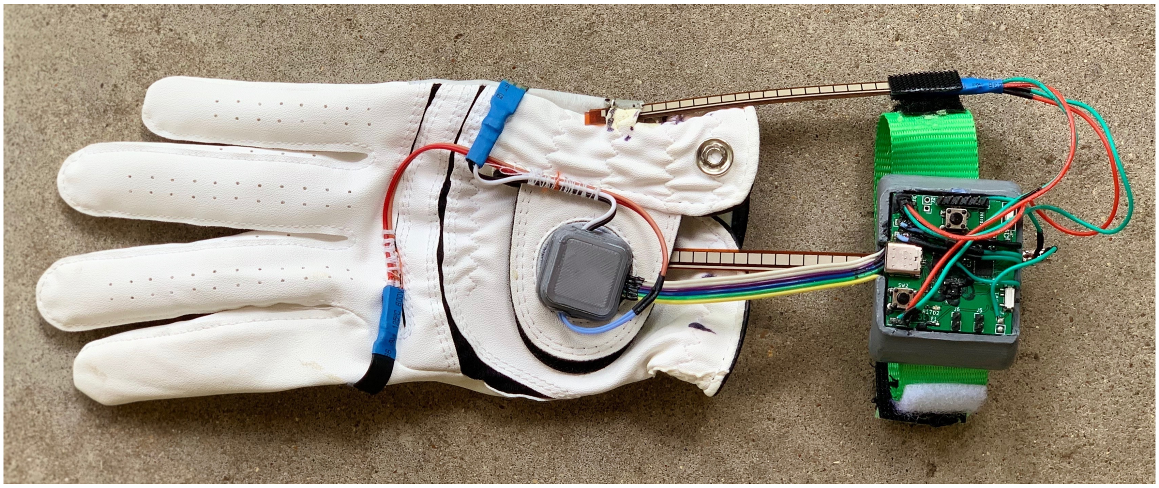

Figure 1.1

The proposed solution, a sensor-packed golf glove.

differentiate a slice from a straight shot. A slice is a specific flight pattern of a golf shot; the three basic flight patterns—hook, straight, and slice—are seen in Figure 1.2. A slice also happens to be the most common non-straight flight trajectory, which is ideal for data collection.

1.3 Contributions

The principal contributions of this thesis are:

- the use of flex and pressure sensors integrated into an embedded golf glove system.
- the use of a neural network to characterize the efficacy of an embedded device in acquiring data compared to laboratory and professional grade solutions.

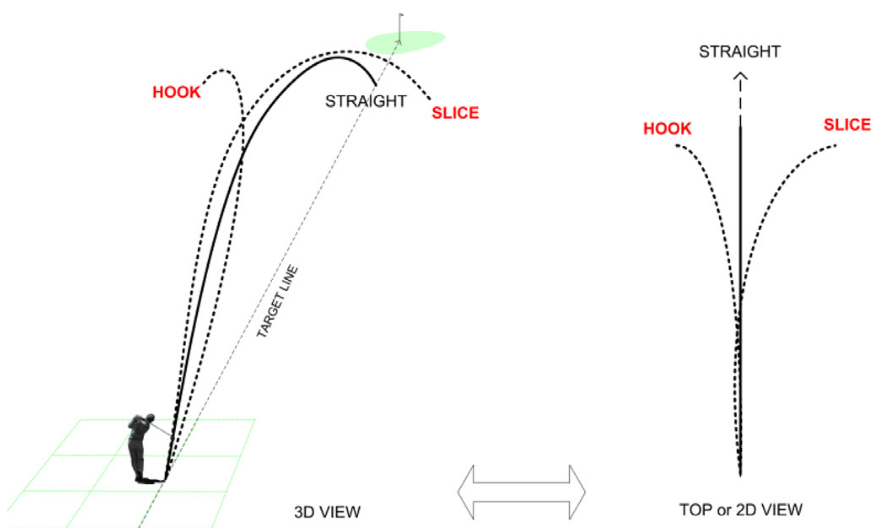

Figure 1.2

Visualization of ball trajectories for the three basic ball flight patterns.

CHAPTER 2

LITERATURE REVIEW

2.1 Motion Tracking

2.1.1 Image-based Motion Capture

As its name suggests, image-based motion capture involves an external imaging device to identify the subject and to record its movements in three-dimensional (3D) space. Such systems are stationary and restricted to laboratory environment, making them ill-suited for instant feedback in any other environment.

2.1.2 Inertial Sensor-based Motion Capture

Inertial sensor-based motion capture involves an IMU that is typically composed of a tri-axis accelerometer and a tri-axis gyroscope. Together, they form a 6 degrees of freedom sensor that, when given a single initial position, can be used to calculate the object's position in 3D space.

Fortunately, the miniaturization of complex components like IMUs into micro-electromechanical systems (MEMS) sensors and the increasing computational power of embedded microcontrollers opens up new opportunities for motion capture. A few commercial groups have brought to market golf training devices using these low-cost MEMS sensors attached to the club shaft and grip [1, 17], but these devices have not been validated [13]. Research groups are also using inertial sensors in the golf realm to detect a swing [8], record and analyze a swing [10, 13], and analyze a putting motion [9]. Kos and Kramberger are taking a more general approach by incorporating an IMU into a system that records movement and biometric information during sport activities [12].

2.2 Machine Learning

Machine learning, a subset of artificial intelligence, refers to a group of algorithms that automatically "learn" from data by inferring patterns [5]. These algorithms are extremely useful for solving problems that are too complex to code directly. In supervised learning, one type of machine learning task, the algorithm is given a set of accurate input and output pairs, called training data, from which to learn. During training, supervised learning algorithms create a mathematical model or function to consistently solve the given problem with the expected output. Once the model is trained, it may be used to predict the output of inputs it has never seen before.

Classification algorithms, which categorize inputs into a finite set of output possibilites (e.g., straight or slice), are a type of supervised learning.

Neural networks (NN) are a class of general function models that are loosely based on biological neural systems. NNs are used extensively in machine learning tasks since they can theoretically approximate any continuous function. Deep NNs, which have multiple hidden layers, are especially popular since they accel at learning complicated patterns. NNs have been used to predict golf ball trajectory [2] and to recognize general human motions [16].

When dealing with time series, a type of network called a recurrent neural network (RNN) is often utilized. The cyclic nature of RNNs allows them to periodically or repeatedly apply certain calculations to time series data.

2.2.1 Topology

The basic elements of the proposed RNN are the long short-term memory (LSTM) layer, a fully connected layer, a softmax layer, and a cross-entropy output layer.

LSTM layer LSTM elements were proposed in 1997 by Hochreiter and Schmidhuber [7]. They are used to effectively recognize patterns from an arbitrary time in the past. The topic's classic explanations are Graves's explanatory thesis [6] and Olah's blog post [14].

Fully connected layer A fully connected layer consists of neurons that each have weighted connections for every input and a bias. These weights and biases are used to calculate the strength of input received by each neuron. A weight is a measure of importance of the corresponding connection and is typically restricted to the range $\boldsymbol{w} \in [-1, 1]$. A bias sets an activation threshold for each of the layer's neurons, allowing each neuron to activate at a unique level of input.

From a mathematical perspective, if the layer has N inputs and M neurons, the layer's weights can be represented as an $N \times M$ matrix $\boldsymbol{w}$ and the layer's biases as an array $\boldsymbol{b}$ of length M. In other words, neuron i has a corresponding array of weights $\boldsymbol{w}_i$ of length N and a single bias term b_i. Given an input vector $\boldsymbol{x}$, the output of neuron i can be represented by Equation (2.1).

$$y_i = \boldsymbol{x}^\top \boldsymbol{w}_i + b_i \tag{2.1}$$

Neurons are typically initialized with zero bias and weights with a random Gaussian variable with standard deviation 0.01.

Softmax layer The softmax layer takes an input of K real numbers and normalizes it into K probabilities. This makes it ideal for classification methods, whose whole purpose is to determine the probability that a network input belongs in a certain output class. The softmax layer maps the non-normalized output to a probability distribution over the output classes. It has a neuron for each output class; in the proposed case, one for straight and one for slice. The softmax layer with K neurons can be represented functionally according to

$$P(y = j \mid \boldsymbol{x}) = \frac{\exp(\boldsymbol{x}^\top \boldsymbol{w}_j)}{\sum_{k=1}^{K} \exp(\boldsymbol{x}^\top \boldsymbol{w}_k)} \tag{2.2}$$

where y is the output, $\boldsymbol{x}$ is the input vector, and $\boldsymbol{w}$ is the weight matrix.

Cross-entropy output layer The cross-entropy output layer takes the output of the preceeding softmax layer that estimates a class given the inputs and calculates the model's predictive discrepancy, or loss. The cross-entropy loss function heavily penalizes network results where the predicted output $\hat{y}$ differs from the observed true value y and heavly favors results where these are the same, according to

$$L = -y\log(\hat{y}) - (1-y)\log(1-\hat{y}) \tag{2.3}$$

For a multi-class problem, the loss at each output neuron is averaged according to Equation (2.4) before propogating back through the network to optimize it by adjusting weights and biases.

$$L = -\frac{1}{n}\sum_{i=1}^{n} y_i\log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i) \tag{2.4}$$

The proposed network is trained using backpropagation solvers such as ADAM or stochastic gradient descent. Classifying neural networks use training data (inputs and output labels) to adjust all of the weights in the network until results are consistent. The results depend heavily on the training data, the network topology, the solver, the solver parameters, etc. Unfortunately, there are no one-size-fits-all networks and lots of parameter tweaking is usually required.

The network topology used in this analysis, from input to output, is: input, bi-directional LSTM, fully connected, softmax, and cross-entropy output. Figure 2.1 is a diagram of the network topology. In Matlab code:

```
layers = [ ...
    sequenceInputLayer(inputSize)
    bilstmLayer(numHiddenUnits,‘OutputMode’,‘last’)
    fullyConnectedLayer(numClasses)
    softmaxLayer
    classificationLayer]
```

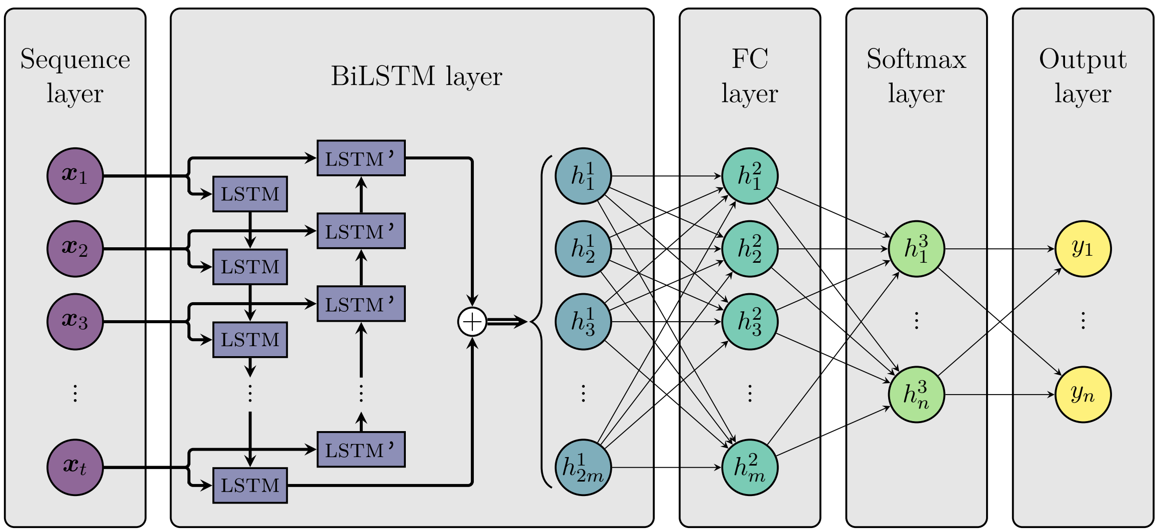

Figure 2.1

Neural network topology with t timesteps, m inputs per timestep, and n output classes. A single line bold connection indicates a vector of length m, a double line bold connection indicates a vector of length $2m$, and all other connections are passing scalar values.

CHAPTER 3

GLOVE SYSTEM

The proposed system is a glove-based device designed with the average golfer in mind. The initial development of the glove system was completed as part of a two-semester group design project [3, 11]. The design's main non-technical constraint was to be unobtrusive to the user in order to not interfere with performance.

Further development was conducted to add features, fix bugs, and increase reliability in order to facilitate this structured evaluation. There were three major software features added: attaching an accurate real time value to each data reading using real-time clock, a primitive swing detection algorithm, and an internal swing buffer that is filled once a swing is detected. The major bugs that were fixed included an unreliable Bluetooth connection and an insufficient database storage throughput.

Shown in Figure 3.1, the device is logically split into three subsystems: glove, wrist controller, and software application. In the following sections, these subsystems and their interactions are described in detail.

3.1 Glove Subsystem

The glove subsystem consists of the glove garment, linear flex sensors, flexible pressure sensors, an IMU, and electrical connector components. This garment func-

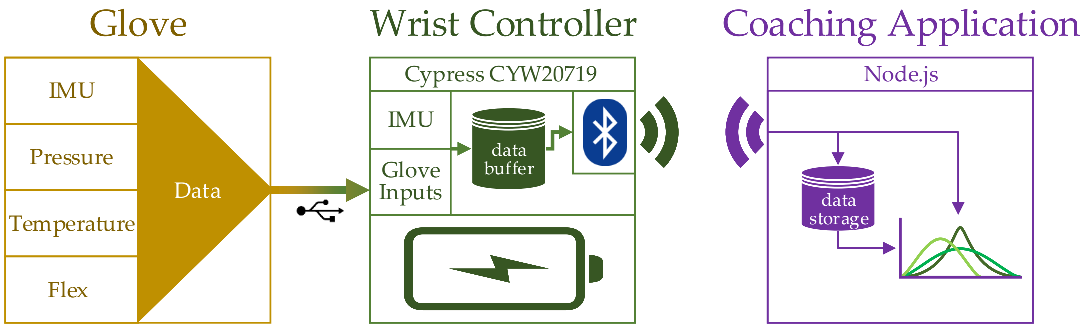

Figure 3.1

System Overview

tions as a mounting surface for the various sensors. These sensors will receive power and transfer data to the controller through the electrical connector mounted on the glove.

The IMU collects linear acceleration and angular velocity of the top of the hand. Linear acceleration measurements have 16-bit resolution per axis and measuring ranges of $\pm2/\pm4/\pm8/\pm16$ g. Angular velocity measurements also have 16-bit resolution per axis and measuring ranges of $\pm245/\pm500/\pm2000$ dps.

The two flexible sensor types on the glove are what differentiate it from other commercial products. They are situated between the glove and the wrist controller to precisely measure the critical wrist flexion of the swing. On either side of the palm are two pressure sensors, which measure the grip pressure exerted on the club. The two pressure sensors may prove useful in preventing injury caused by forceful or imbalanced gripping of the club.

3.2 Wrist-mounted Controller Subsystem

The wrist-mounted controller contains a second IMU, a microcontroller, and a Li^+ battery. The wrist-mounted controller is responsible for collecting, buffering, and transmitting data via Bluetooth to the software application. Table 3.1 lists the fields and byte sizes of the data frame. For the data collection, the device is programmed to poll at a 200 Hz sample rate.

Table 3.1

Data frame structure.

data	bytes
`time`	4
`pressure1`	2
`pressure2`	2
`flex1`	2
`flex2`	2
`wristAccelerationX`	2
`wristAccelerationY`	2
`wristAccelerationZ`	2
`wristRotationX`	2
`wristRotationY`	2
`wristRotationZ`	2
`handAccelerationX`	2
`handAccelerationY`	2
`handAccelerationZ`	2
`handRotationX`	2
`handRotationY`	2
`handRotationZ`	2

3.3 Software Subsystem

The application's responsibilities are managing the Bluetooth connection with the device and processing data. Upon receiving data from the wrist-mounted controller, the application processes and stores it in a SQLite database. The application also exposes a web interface that is used to initiate and control the Bluetooth connection to the device.

CHAPTER 4

METHODS

To evaluate the efficacy of the proposed solution, it was compared to the gold standard of kinematic recording: motion capture. Specifically, the two systems were measured in their ability to distinguish a slice from a straight swing.

4.1 Setup

Two volunteers were recruited to produce the volume of swings for the model. One volunteer was a seasoned golf instructor with a straight swing, while the other was a consistent slicer.

4.1.1 Motion Capture

Due to the stationary nature of image-based motion capture systems, the testing occured in a motion laboratory outfitted with a Vicon Motion Capture system [15]. The Vicon Motion Capture system uses the same sampling rate as the glove: 200 Hz. A few of the systems cameras can be seen in the upper middle to upper right of Figure 4.1.

Figure 4.1

Data collection in progress.

4.1.2 Launch Monitor

In order to classify the swings as slices or straight shots, each swing was also recorded with a Foresight GC2+HMT Launch Monitor [4]. A Launch Monitor, seen in Figure 4.2, is a high-speed camera system that measures the impact and launch of the ball. It uses club face and ball metrics to determine the swing's contact efficiency and to predict the ball's flight trajectory. Since these metrics and the predicted trajectory describe the outcome of the swing, they were used to verify that each swing from the participants was representative of their expected swing pattern: slice and straight.

Figure 4.2

Foresight GC2+HMT Launch Monitor.

4.1.3 Miscellaneous

Two other items that facilitated indoor testing were a large archery backstop net to catch the balls and an artificial turf mat to mimic an actual golf setting. Both can be seen in Figure 4.1

4.2 Procedure/Data Acquisition

In an effort to eliminate variability, the participants used irons with about 30° loft on the club head; one participant used a club with a loft of 30° while the other used a club with a loft of 30.5°. This difference in loft is negligable considering iron sets have about 4° between each club. This would be equivalent to one participant using a 6-iron and the other participant using a $6\frac{1}{8}$-iron from the same set. They could not use the same club since they required different club lengths.

Once acquainted with the laboratory setting and their role, participants donned the motion capture sensors and the glove system. After a few warm-up swings, they each produced around 50 recorded swings like the one in Figure 4.1. While some were total shanks and others were not recorded properly by the motion capture system, the majority of recorded swings were quality inputs for the model.

4.3 Data Visualization

Figure 4.3 depicts the glove's recorded acceleration *vs.* time relationship during a swing. Similarly, Figure 4.4 depicts the glove's angular velocity *vs.* time relationship. Figures 4.5 and 4.6 show the flex and pressure data *vs.* time, respectively, from the glove system during a swing. The point of impact for this swing is at about 2.0 seconds.

4.4 Data Analysis

The motion capture data set consisted of 6 input vectors for each swing: wrist flexion, wrist deviation, forearm linear acceleration, forearm angular velocity, hand linear acceleration, and hand angular velocity. The glove data set consisted of 16 vectors: all measurements in Table 3.1 except for time. This difference in input dimensions requires the two models to have slightly different network topologies.

Matlab was used to analyze the two data sets. Each data set was divided into disjoint training and testing data sets. The code trained the network with the training data and then tested it's accuracy using the testing data. This process was repeated a total of 10 times.

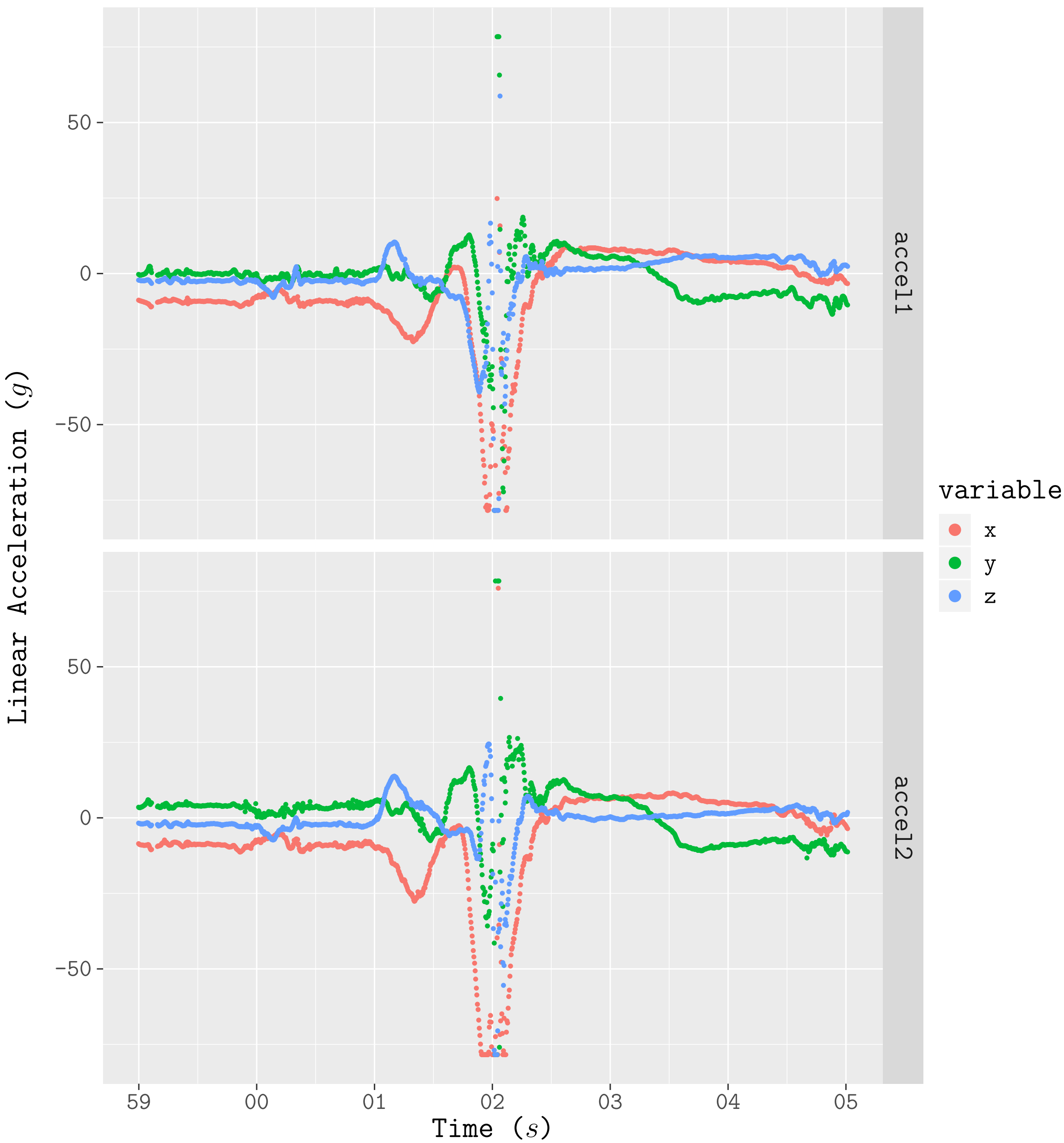

Figure 4.3

IMU accelerometer data from a single swing.

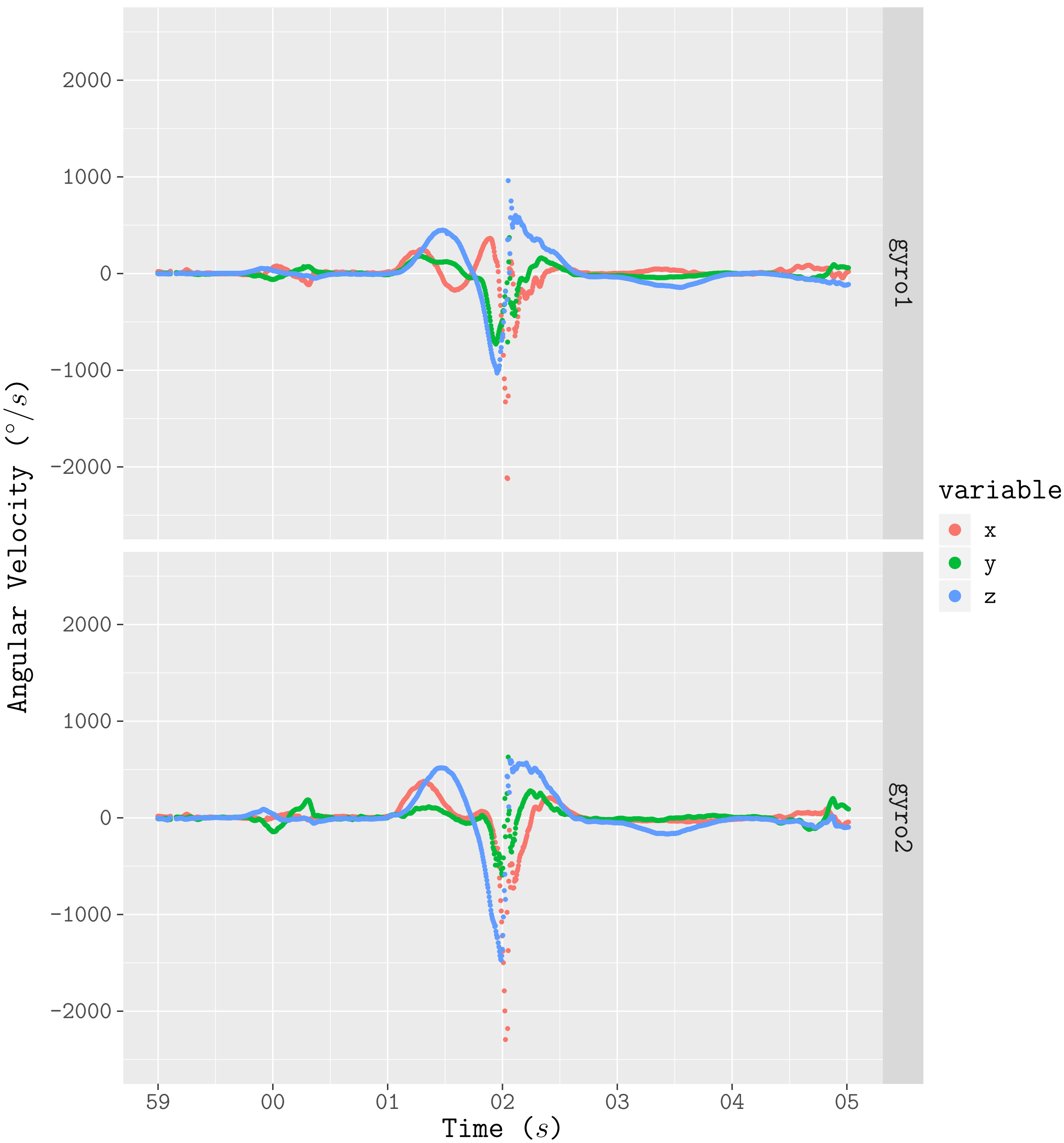

Figure 4.4

IMU gyroscope data from a single swing.

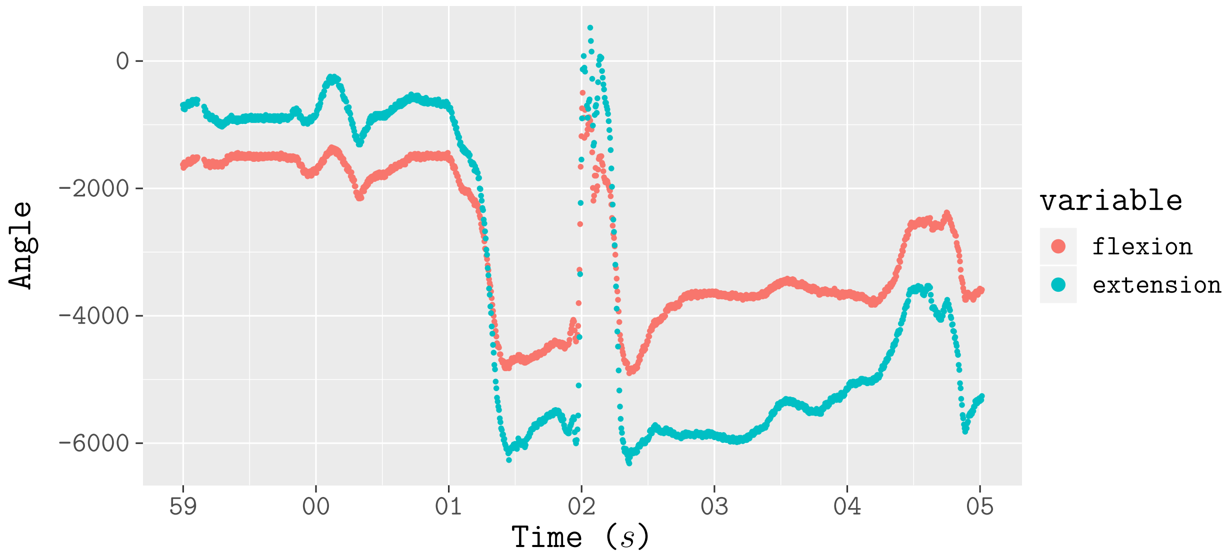

Figure 4.5

Flex sensor data from a single swing.

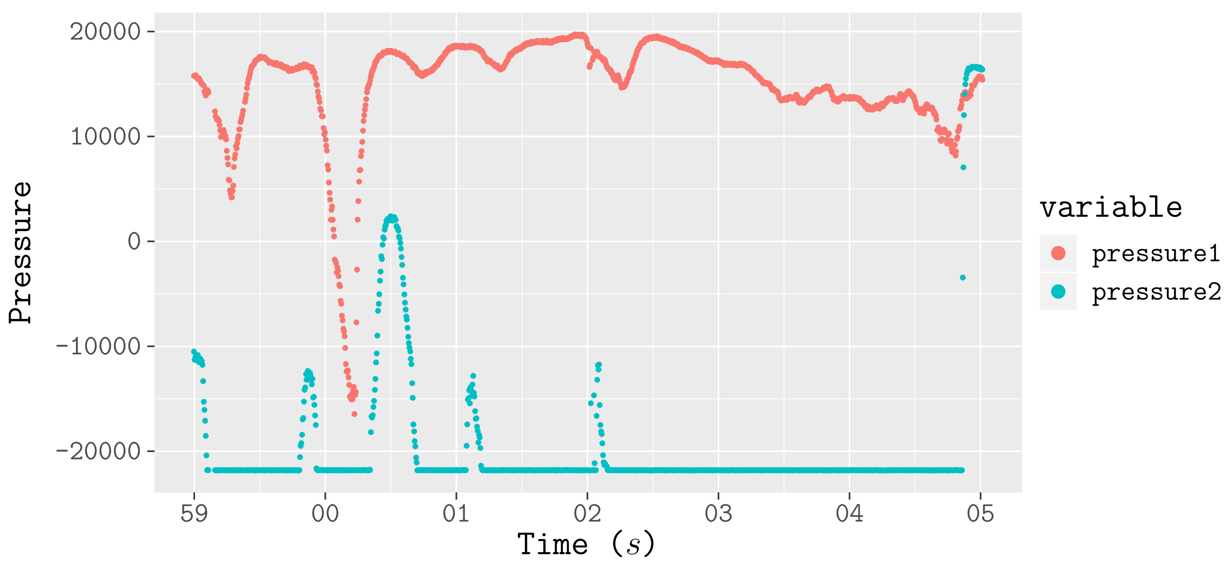

Figure 4.6

Pressure sensor data from a single swing.

CHAPTER 5

RESULTS

This section reports on the training and testing of the RNN topology discussed in section 2.2. The results for 10 iterations of the motion capture model and the glove model are found in Tables 5.1 and 5.2, respectively.

Table 5.1

Motion capture model results.

iteration	training accuracy (%)	testing accuracy (%)
1	97.44	91.89
2	100.00	97.30
3	100.00	94.59
4	97.44	100.00
5	100.00	97.30
6	100.00	97.30
7	100.00	97.30
8	97.44	94.59
9	100.00	97.30
10	97.44	94.59
avg	98.97	96.22
var	1.75	5.19

The glove model averaged 3.29% lower training accuracy and 2.05% lower testing accuracy compared to the motion capture system. The motion capture system was

Table 5.2

Glove system model results.

iteration	training accuracy (%)	testing accuracy (%)
1	97.30	91.67
2	94.59	94.44
3	97.30	97.22
4	94.59	88.89
5	97.30	94.44
6	94.59	97.22
7	94.59	88.89
8	94.59	94.44
9	94.59	97.22
10	97.30	97.22
avg	95.68	94.17
var	1.95	11.06

slightly more accurate, but the proposed device is unrefined and still in the prototyping and testing phase of development.

5.1 Analysis

Using a two-sample Kolmogorov-Smirnov hypothesis test of the two testing accuracy samples, the resulting p-value was 0.0547. At a 95% confidence level, the hypothesis test does not dismiss the idea that the two testing accuracy samples are from the same distribution. In other words, the glove model may be statistically equivalent to the motion capture model.

5.2 Limitations

The small number of model iterations limits the statistical significance of any statistical analysis. Each model could be run hundreds of times in order to give more statistically significant results. In the same way, the results are limited by the low quantity of input swings; the models would be better trained and thus more robust if given more swings to analyze.

CHAPTER 6

CONCLUSION

This study demonstrated the efficacy of the glove device in capturing human motion during a golf swing. In doing so, it confirmed the device's viability as an economical alternative to professional training devices.

The studied solution leverages an embedded system and machine learning, which are both important areas of study in computer engineering. The machine learning analysis in this study opens the door for the verification of other motion-capturing embedded systems. Being able to verify the ability of motion-tracking embedded systems will ensure a level of quality in the products and experiences they enable.

6.1 Future Work

In terms of methods, future research includes addressing the limitations from section 5.2: gather more swing data from multiple participants and run the two neural network models for hundreds of iterations. Additionally, tweaking the neural networks' parameters may improve results.

In terms of the glove device, development is still in progress. One fixable flaw is that its two IMUs are clipping at $\pm 8g$; they ought to be reconfigured in firmware to a larger range of $\pm 16g$. Another improvement to eliminate Bluetooth connectivity issues would be to implement a mobile application; mobile phones are more portable and have a more stable Bluetooth stack compared to a laptop computer. On the hardware side, the device could be improved with the addition of on-board flash memory (e.g., an EEPROM or SD card) which would allow more options for recording and buffering data.

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