Brave Virtual Worlds: Implementation of Motion Capture Methodologies for Predictive and Preventative ACL Rehabilitation

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Brave Virtual Worlds: Implementation of Motion Capture Methodologies for Predictive and Preventative ACL Rehabilitation

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Abstract

The ability to track and monitor injurious biomechanical movement patterns has become a critical area of development in the fields of sports and rehabilitation. Lower extremity injurious movements have been linked as risk factors associated with anterior cruciate ligament (ACL) injuries. With an annual incidence rate of 200,000 to 400,000 cases in the US, ACL rupture is a common problem in younger populations participating in medium to high intensive activities. While surgical reconstruction is commonly done for such injuries, the ability restore normal joint function and mitigate long-term development of early onset osteoarthritis is difficult to understand. However, through the study of ACL injury mechanisms, there may be the development of a process to design training programs aimed at prevention. This involves objective observation of contributing motions that occur causing an ACL rupture. One common example is the dynamic knee valgus collapse, which is usually described as excessive medial collapse of the knee. The aim of the following project was to use a custom on-body motion-capture wearable to gather data on the dynamic knee valgus collapse. The data was then analyzed using various machine learning algorithms to determine the accuracy of classifying a knee valgus collapse versus a normal knee abduction including K-Nearest Neighbors, Logistic Regression, and a Recurrent Neural Network called the Long Short-Term Memory algorithm. The testing accuracy of each model was compared against that of the current research standard of detecting human movement patterns, the K-Nearest Neighbors model. The Long Short-Term Memory algorithm demonstrated the highest level of accuracy statistically significant at a p-value of 0.01891 with a Logistic Regression model demonstrating a mean time of classification of 0.0004 s. Thus, the use of an on-body motion capture wearable paired with machine learning based classification can provide an effective and cost-efficient methodology for ACL injury preventative care.

Keywords: ACL, motion capture, machine learning, preventative care, dynamic knee valgus collapse

Introduction

Anterior Cruciate Ligament (ACL) rupture is a common orthopedic injury suffered as a result of sports participation. There are over 200,000 to 400,000 cases of ACL rupture in the U.S. alone where 70% of these are non-contact (without direct blow to the knee) based and these types of injuries are considered the most predominant method mechanism of the injury itself [1]. These include injuries that occur during jumps or lateral cutting maneuvers during athletic activities where dynamic neuromuscular control deficits can cause eventual ACL rupture [2]. Furthermore, there is approximately a two to eight times higher risk in female athletes compared to male athletes [3]. Currently, the "typical" patterns of an ACL rupture is defined as a low-velocity twisting injury or valgus/external rotation strain followed by immediate pain and swelling which implies hemarthrosis. One common example of such a movement pattern is the dynamic knee valgus collapse, or the excessive medial collapse of the knee [4].Some major repercussions following an ACL injury include temporary or long-term disability, absence from other activities, high costs from operative or rehab treatment, and early onset osteoarthritis (OA) [5].

The current treatment recommended following ACL rupture is surgical reconstruction in order to facilitate a return to desired daily activities, including sports. However, the estimated annual health-care cost of these surgeries is approximately $3 billion in the U.S. alone. The decision to recommend this operative reconstruction is multi-factorial and individualized to each patient. Still, following ACL reconstruction many athletes fear return back to their intensive sports activities due to reinjury concerns [3]. Thus, a new focus has developed to potentially track and prevent lower extremity injurious movement patterns that may be a cause of future ACL rupture, such as the dynamic knee valgus collapse. A gold-standard method seen today is using reflective anatomical markers which are then recorded using highspeed motion analysis camera systems which are commonly referred to as optical motion capture (OMC) systems [1]. These systems present not only the ability to track position but also attitude (posture) of the movements along with accounting for issues with drift that were common with on-body motion capture systems [6]. While OMC systems are considered gold-standard when it comes to tracking and monitoring human motion, they have many drawbacks as well. Not only are these systems extremely expensive but they are also limited in terms of their use off the field for athletes who are usually injured when on the field. Furthermore, most OMC systems today have one other common problem: they are unable to get an accurate sense of joint angle measurements which leads to the infeasibility of creating accurate 3D-model reconstructions for further analysis. This applies primarily to marker based OMC systems where marker-less (use of just cameras) systems rely heavily on the resolution of the camera and may face occlusion problems thus not actually detecting the object to be tracked [7].

By using on-body 9-axis inertial motion units/sensors or IMUs our group will be able to solve many of the problems associated with the gold standard OMC systems. This first includes that the cost of these on-body sensors are drastically lower than purchasing multi-camera setups to track human motion. Second, prior research into IMU development for tracking human motion has solved many of the drift and calibration problems of the sensors that were originally present [8]. With this massive improvement, these on-body systems provide more accurate readings of joint angles which can then be implemented even further to not only capturing human motion but also using machine learning to predict or detect potential movement patterns. Lastly, the use of a cheaper, smaller, and accurate on-body motion capture system provides the ability to be used anywhere at any time, especially on the field for athletes.

In regards to utilization of machine learning on top of data collected from an on-body motion capture system, currently the analysis of human motion is limited to the classification of discrete movement patterns or recognition of human motion itself such as walking vs. sitting. There is a limited scope of work when it comes to predicting the onset of a specific movement pattern and the severity with which it may occur. Current classification models used for human motion include those based on Human Markov Models (HMMs), the K-nearest neighbors (KNN) algorithm and support vector machine (SVMs) [9]. However, there are a limited number of studies analyzing the accuracy of the various classification methods present in machine learning literature along with no models present to analyze the prediction of the onset of specific movement patterns over time. Some of the current models implemented in prior studies as mentioned above will be used as a standard accuracy value to which compare to for all the other models. Algorithms such as long short-term memory (LSTM) which is a type of recurrent neural network (RNN) or a multi-layer perceptron (MLP) demonstrate a greater accuracy with the analysis of the features extracted from the on-body motion capture system.

Thus, the motion-capture paired with machine learning driven software capstone project will initially complete the testing of a custom wearable, the selection of a controlled exercise to determine classification of a dynamic knee valgus collapse or an injurious movement pattern associated with an ACL rupture, and confidence in the data collection capability of the wearable. Additionally, the capstone project will then delve into the comparison of various machine learning models to classify the onset of a knee valgus collapse on in-house collected datasets in preparation for an IRB approved biomedical pilot study with a team of physical therapists at Mary Baldwin University in Staunton, VA.

The work of this project was also performed under the umbrella of a UVA student-led startup, Brave Virtual Worlds LLC. This venture aims to develop a motion-capture platform to be used by athletes across sports to help increase performance and reduce avoidable injuries.

Results

Testing of On-Body Motion-Capture Wearable

The project entailed using a custom motion-capture wearable developed by a research group within the UVA Electrical & Computer Engineering department. Through the use of a mobile application paired with the wearable, functionality tests were conducted to ensure that the device was in fact able to relay spatial and motion data relative to real-world observations. This included testing the device twice via a member of the Brave Virtual Worlds startup

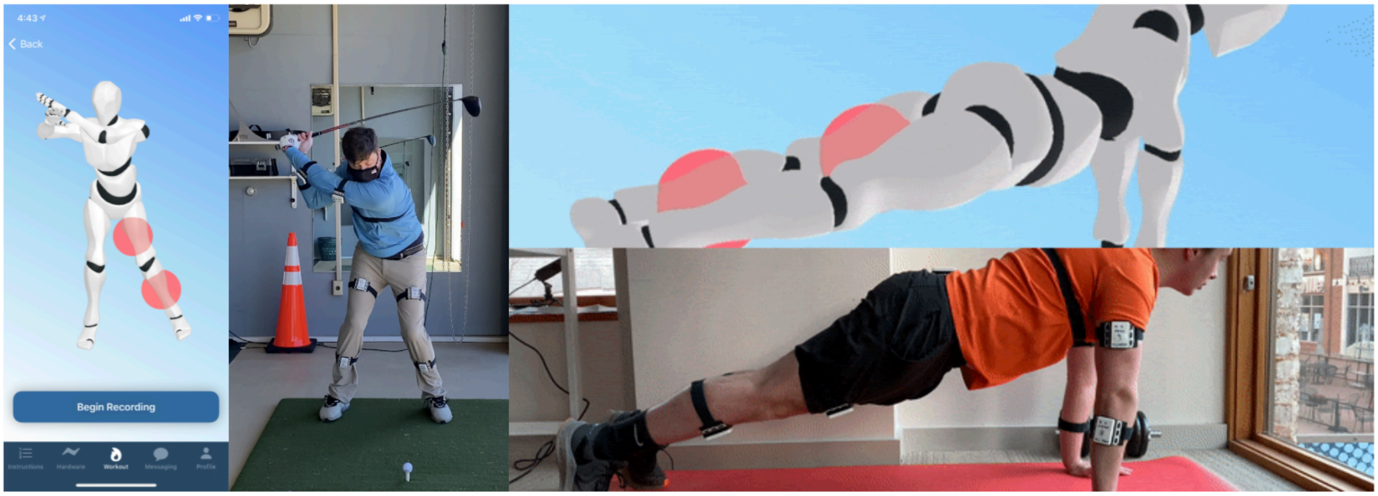

Fig. 1. Images of testing custom motion capture wearable. The wearable was tested on both a member of the Brave Virtual Worlds team and a golfer at The Club at Glenmore to determine spatial and motion data functionality relative to the real world. The images depict both a person wearing the wearable along with a 3D representation on a custom mobile application developed for the device.

team and on the field with a pro-golfer at The Club at Glenmore in Crozet, VA (**Fig. 1**). These resulted in determining that the global position and orientation of the data sent from the wearable were in fact in accordance to the real-world by observing a 3D simulation.

Selection of Controlled Exercise and Data Validation

An exercise was selected to conduct an exploratory study of whether or not the proposed on-body motion capture system can detect a dynamic knee valgus collapse. A prior study demonstrated the use of the single-limb step down exercise in females between the ages 20-30 to assess the relationship between frontal-plane hip and knee angles, hip-muscle strength, and electromyographic (EMG) recruitment [10]. This similar methodology was used as an exercise protocol for the use of the proposed technology. Following establishing this protocol, the on-body motion capture system was assessed on members of the capstone project performing a normal single limb step-down and valgus-collapse single-limb step down. This determined if the data being read from the motion capture system is in the correct orientation and can actually detect the event of a single-limb step down exercise. The data specifically focused on was that of the sensor attached to the lower leg below the knee.

The dataset collected exhibited a clear pattern of a single limb-step down both during the step-down and the step-up (**Fig. 2**). This pattern was most clearly seen in the w-, x-, and z-axes of the quaternion or spatial data obtained which illustrates that the data can in fact be used for pattern-based classification. The y-axis demonstrated the most noise which was attributed to the fact that this axis is the most sensitive when performing the single-limb step down according to how the sensor was placed on the leg.

Machine Learning Implementation

Following validation of the data being collected, over 100 preliminary datasets were collected via the team of physical therapists at Mary Baldwin University. These datasets were then processed and analyzed through four main machine learning algorithms: KNN, Logistic Regression using scikit-learn, a custom Logistic Regression using gradient ascent, and LSTM. All of these models required normalized

data, where the spatial data was normalized between 0° and 180° for the conversion to Euler angles from the spatial data obtained as raw values from the motion-capture wearable.

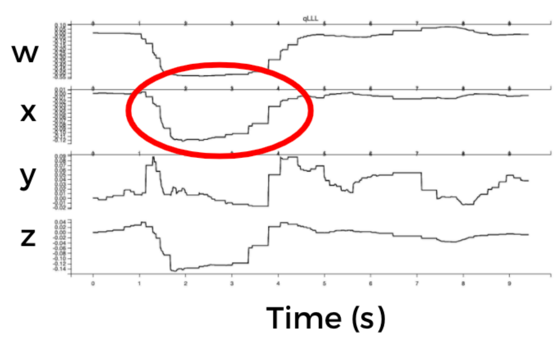

Fig. 2. Representation of Quaternion Data. This illustrates the 4 axes of data collected from one motion capture sensor and how it shows a pattern following that of a single-limb step down exercise as highlighted by the red portion.

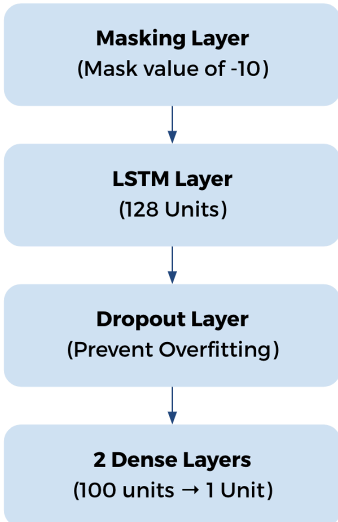

Fig. 3. LSTM Model Architecture. This flowchart illustrates the breakdown of the five layers used to compose the LSTM model: Masking layer, LSTM layer, Dropout Layer, and two Dense layers

The KNN algorithm utilized Euclidean distance as the metric of distance between neighboring data points which is how the model evaluates which class a new data point falls under. It was evaluated using 5-fold cross validation to ensure that the algorithm was not over or underfitting the data. This model provided a standard to compare against for mean testing accuracy, 79.48%.

The Logistic Regression algorithm using the scikit-learn library available in Python. This is an important tool used in simple machine learning analysis to developed black-boxed models without the need of developing custom loss or optimization functions. The custom Logistic Regression algorithm utilized the loss function of gradient ascent which helps maximize the likelihood function of determining the outcome of the model, in this case a linear regression line acting as a boundary between the two classifications of valgus collapse and normal knee abduction. Both of these algorithms demonstrated the fastest times when it came to classifying new data, 0.0051 s for the scikit-learn based model and 0.0004 for the custom model.

The LSTM model architecture was broken into 5 layers, a simple model for preliminary analysis of time-series spatial data and was developed using the industry standard machine learning analysis libraries in Python, Keras and Tensorflow (**Fig. 3**). The first layer was a masking layer that eliminated a masking value of -10 which was done on the datasets to ensure that each set was the same length when processed into the LSTM model. The next layer was an LSTM layer consisting of 128 units which was the average dimensionality of the output space. The following layer was a Dropout layer that served the purpose of minimizing potential overfitting of the model onto the data. Lastly, two Dense layers were added to actually perform the final binary classification of each dataset as a valgus collapse or normal knee abduction. This model resulted the highest accuracy of all four models, with a mean validation accuracy of 88.75% and mean testing accuracy of 90.00%.

All of the metrics used to compare each model are summarized in Table 1. This table looked at mean validation accuracy to ensure that each model was appropriately evaluating the data, mean testing accuracy as the primary metric, the mean F1 score which is a metric that encompasses both precision and recall of a machine learning model, and the mean time it takes for each model to classify new data. The means were taken over five trials of running each model.

Table 2. Summary of Metrics for Machine Learning Models. This table shows the four metrics used to compare across models. Accuracy was gauged via the mean validation and testing accuracies, the F1 score provided precision and recall, and mean testing time indicates real-time implementation capability.

Algorithm	Mean Val. Acc (%)	Mean Testing Acc. (%)	Mean F1 Score	Mean Testing Time (s)
KNN	79.07	79.48	0.7630	0.0217
Logistic Regression (scikit-learn)	82.00	76.31	0.8093	0.0051
Logistic Regression w/gradient ascent	81.01	78.42	0.8048	0.0004
LSTM	88.75	90.00	0.8683	1.116

The mean testing accuracy metric was then used to run multiple paired t-tests to compare each model to the research standard, the KNN algorithm (**Fig. 4**). The statistical results demonstrated that the only model statistically significantly different was the LSTM model with a p-value of 0.01891 ($\alpha = 0.05$).

Discussion

The novel methodology of using a custom on-body motion capture wearable paired with assessment of various machine learning models provides a new way of preventative care for ACL ruptures or injuries. As discussed in this paper,

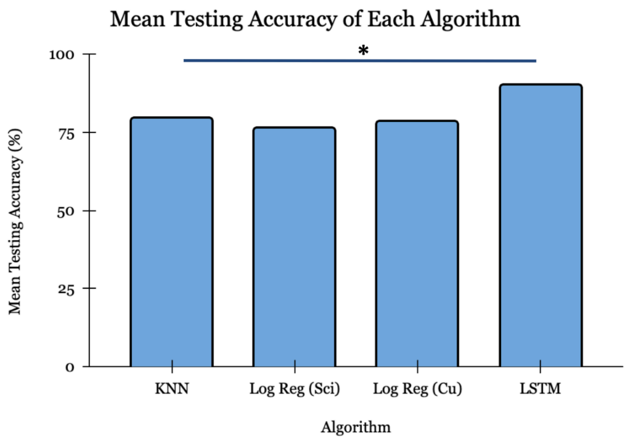

Fig 4. Bar chart of mean testing accuracies of each model. This graph illustrates the results of each paired t-test run against the standard KNN model with only the LSTM model demonstrating a statistically significant difference (* = statistically significant with $p \leq 0.05$)

the project completed testing of the custom wearable through functionality testing followed by selection of a controllable exercise and assessing data collection capabilities. Afterwards, four machine learning models or algorithms were compared to determine the efficacy of using machine learning in detecting or classifying the onset of a specific movement patterns, in this case the dynamic knee valgus collapse. The project exemplified the use of both research and industry standard data analytics for classifying human motion towards the detection of injurious movement patterns.

The wearable was determined to be functional in accurately detecting spatial orientation of a user and their motion which was validated by the initial dataset collected on a single repetition of a single-limb step down exercise. This ensured that the wearable was usable as an analytical tool similar to that of OMCs or marker based tracking.

Following this validation, the implementation of various machine learning models provided insight into how further analysis of the data collected can truly provide a way of detecting the onset of injurious movement patterns in an almost real-time instance. First, the implementation of the KNN model provided a baseline against which other models were compared against due to its prevalent use in current literature as a standard for detecting human motion. This involved outputting various metrics to gauge the differences between the models, including the mean validation/testing accuracies, the mean F1 scores, and mean testing times. Following these results, paired t-tests determined that the LSTM model presented the most different and accurate algorithm achieving an average accuracy of 90% relative to the ~79% seen when using the KNN model. However, the LSTM model was also the slowest when it came to testing it on new data points, with the fastest models being the two Logistic Regression models.

Thus, the results demonstrated that machine learning is in fact a viable option when used to classify or even predict specific movement patterns. With LSTM, there are further possibilities of using complex neural network based models to further improve the accuracy, and the option of using new models such as Gated Recurrent Units (GRUs) which is another recurrent neural network more favorable towards smaller datasets. The main difference between both algorithms is that that GRU has two gates (reset and update) and LSTM has three gates (input, output, and forget) thus indicated that GRU has a less complex structure and more computationally efficient since it does not require a memory unit.

Furthermore, with this novel methodology on using on-body motion capture for preventative care purposes, new work can be performed on attempting to scale machine learning across multiple injurious patterns, not just the dynamic knee valgus collapse. Since the wearable encompasses the full body, it is possible to analyze each joint for potential movement issues to prevent injuries across the whole body.

Overall, the project presented an affordable and efficient way of using motion capture to understand the kinematics of movement patterns that can lead to an ACL rupture. Under the umbrella of a UVA student startup, this research will also be applied within the product offerings of said startup to create a large motion capture platform capable to helping those participating in intensive activities to either improve their performance and even prevent injuries.

Materials and Methods

The following are the methods followed to produce the results seen in this paper, including the brief methodology used to design the motion capture wearable utilized in this project.

Development of Motion Capture Wearable

The on-body motion capture wearable was designed using custom electronics developed by a research group within the

UVA Electrical and Computer Engineering department under the guidance of Harry C. Powell Jr. It was developed using KiCad for drafting the schematic of the electronics and sourcing parts from DigiKey. The electronics were then assembled locally in Charlottesville, VA at WWW Electronics Inc. Following manufacturing of the electronics, the housing frame for each one was designed in Autodesk Fusion 360 and 3D printed using both polylactic acid (PLA) and thermoplastic polyurethane (TPU). The medical-grade Velcro bands were sourced from FASTENation INC. to ensure maximum ergonomics when putting on the wearable.

Machine Learning Implementation

Each machine learning model was implemented using custom written Python scripts in VSCode. The main libraries used to implement each model were the following: Scikinematics for understanding spatial (quaternion) data, Numpy, Matplotlib, Scikit-learn, Keras, and Tensorflow. All of the data used for each model was processed into Euler angles: yaw, pitch, and roll. The data was also normalized. The mean of each dataset for each angle was used for the KNN and Logistic Regression models, versus the whole time-series dataset was used for LSTM.

Planned IRB Study with Mary Baldwin University

An IRB approved biomedical pilot study has currently been planned for June 2021 with Mary Baldwin University. This study will use the same exercise, the single-limb step down, to assess the ability of both the on-body motion capture wearable paired with machine learning versus the classic physical therapy assessment on exhibition of the knee valgus collapse in female subjects. This study will include around 20 subjects broken up into two groups and will occur over a duration of 6 weeks which includes a pre-testing phase, mid-testing phase, and post-testing phase to determine how accurate the wearable plus machine learning was over time and if it was able to improve the form of performing a knee valgus collapse for each subject.

End Matter

Author Contributions and Notes

D.P designed research, D.P performed research, D.P wrote software, D.P analyzed data; and D.P wrote the paper.
The authors declare no conflict of interest.

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