How wearable sensing can be used to monitor patient recovery following ACL reconstruction

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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***Abstract*— Anterior Cruciate Ligament (ACL) reconstructions are among the most common sports medicine procedures performed in the world. Over 100,000 patients in the United States annually elect to have ACL reconstruction (ACLR) in hopes of returning to pre-injury level of activity. In the first two years following an ACLR, patients are at their highest risk for re-injury to both the repaired and contralateral knee. The overall incidence rate of an ACLR patient having to go through a second repair in 24 months is six times greater than someone who has never had an ACL tear. Early detection of functional deficits is vital to optimize post-operative rehabilitation and to restore normal movement patterns in patients, especially in those who are young with continued risk exposure from competitive sports. The decision about when to return to unrestricted physical activity or competitive sports has come under much scrutiny due to the lack of evidence-based criteria that have sufficient predictive value. Current methods of detection require unconventional movements which cannot be done in the early stages of recovery in fear of damaging the newly repaired ligament. The need for a precise, objective, and whole-body approach to movement evaluation is essential for the health and safety of patients recovering from ACLR. The objective of our research is to leverage sensing technologies to monitor patients post ACLR and investigate how body sensors can be used to aid medical decision-making regarding rehabilitation progressions. In our study, patient data, extracted from wearable sensors during several functional assessments, was used for multi-level analysis to extract features indicative of mobility and muscle activation. In conclusion of our pilot, we have identified key features effective in determining patient health post-ACLR and implemented these into a machine learning model to estimate the efficacy of lower-body wearable sensors as a means of assessing patient recovery.**

I. INTRODUCTION

In the United States alone, approximately 150,000 anterior cruciate ligament (ACL) injuries occur every year, translating to over $500 million in healthcare costs [1]. These injuries can be especially detrimental to younger athletes, who must endure not only a 6–9-month recovery and rehabilitation period, but also encounter an increased risk of reinjuring their ACL once they return to competitive sports. One study reported that athletes who were less than 20 at the time of an initial ACL surgery had a subsequent reinjury rate of 28%, approximately six times higher than that of athletes who have not torn their ACL before [2].

A major determinant of the likelihood of reinjury is the rehabilitation process after the initial surgery following an ACL injury. During rehabilitation, patients work with physicians to gradually advance toward walking, running, and eventually playing high-impact sports again. However, each recovery process is unique to the patient and circumstances of the injury, and an incomplete or improper rehabilitation may lead to greater risk of reinjury [3].

Wearable sensors have significant potential for filling these gaps. Wearable sensors can be utilized to monitor rehabilitation progress and provide accurate data to assist in enhancing recovery and reducing reinjury rates. Because they are ubiquitous, they can potentially be leveraged to continuously monitor physical activity, provide more portability than in-clinic/lab instruments, and can be worn over an extended period of time in unrestricted environments.

In our work, we propose to leverage wearable sensors attached to the legs of participants while they complete routine rehabilitation exercises to estimate recovery levels. We propose to analyze EMG and accelerometer sensor signals to isolate key features that can differentiate between healthy participants and patients who had recently undergone surgery. We specifically propose four key categories of features including force and strength, speed, stability, and symmetry.

This research will make the rehabilitation process more ubiquitous. It will take individualized monitoring for rehabilitation purposes to the home. It can be used more continuously and passively for treatment, meaning patients no longer need to schedule appointments at doctors offices, clinics, or labs for testing and measurements.

Our paper is organized as follows: Related work– highlighting some relevant studies done in the field of wearable sensors and ACL rehabilitation, study design– overview of the data collection process, proposed methods– detailing the data processing and statistical analysis of the results, and discussion and conclusion– addressing limitations, future work, and relating the overall findings to other studies. Findings from our study will serve as the initial step in determining feasibility of using body sensors to ubiquitously monitor recovery after ACL reconstruction.

A. Related Work

Wearable sensors have been utilized as a protocol to analyze rehabilitation progress and return to activity assessment following ACL injury. The current post-operative system of rehabilitation has five phases, with the final phase being returning to pre-tear sports and activities. Only in phase four

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does the patient begin to be tested in more game-like scenarios with the focus on being able to fully return pain free. In the current system, the use of sensors is not incorporated until phases three and four [4]. This is often too late in rehabilitation to catch and correct certain altered movement patterns.

The integration of machine learning with wearable technology allows for the possibility to monitor real-time functional movements, workloads, and biometric markers during activities. For example, a 2020 study utilizing inertial measurement unit sensors (IMUs) analyzed six healthy patients and six reconstruction patients through time and frequency domain feature extraction and machine learning models following change of direction activities. A 73.07% accuracy was found in predicting between healthy and post-ACL injury subjects. The results of our study demonstrate the ability of wearable sensors and machine learning approaches to predict post-ACL gait patterns in athletes [5].

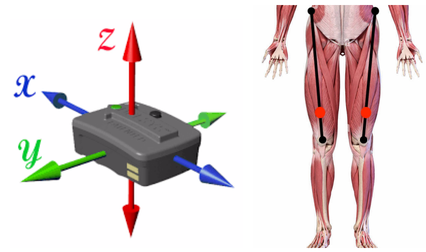
Our study was conducted using electromyography (EMG) and accelerometer sensors. EMG signals measure the muscles response or electrical activity in response to nerve stimulation of the muscle. It is linearly related to the level of muscle contraction as well as the number or muscles contracted [6]. Previously conducted studies have utilized EMG-related assessments on ACLR patients, but they do not assess when a patient is deemed healthy for return to sports. For example, a 2011 study establishes if there are EMG differences after two different surgical graft techniques were used for ACLR. The study found the difference between EMG signals of the two groups to be statistically significant and a predictive method for their analysis [7]. Due to external factors, however, the study was unable to conclude which graft technique is more appropriate.

In addition to studying EMG signals, our study will also be analyzing peak 3-dimensional acceleration signals. This type of signal measures the linear acceleration of the subject along three mutually perpendicular axes. Due to acceleration being proportional to external force, measurement reflects both frequency and intensity of movement [8]. Since a common reason for ACL tears is sudden stopping or change of direction, analysis of knee acceleration in the X-Y-Z direction is very useful. A previous study performed in 2015 examines if biomechanical jumping differences existed between ACLR and non-ACLR subjects after collecting 3D acceleration data using inertial sensors [9]. Significant differences were demonstrated by ACLR patients in relation to the 3-dimensional axis supported accelerations. Our paper will analyze the effectiveness and accuracy of the combination of electromyography, 3-dimensional acceleration, and machine learning approaches to assess overall patient health.

II. Study Design

Twelve ACLR patients and ten healthy patients from the UVA Exercise and Sports Injury Laboratory were recruited to participate in data collection. There were three female ACLR patients and seven female healthy patients. Each participant was fitted with a Delsys Trigno Wireless electromyography and accelerometer sensor to their vastus lateralis on both the ipsilateral/ACLR and contralateral knees. For ACLR patients, the knee that had undergone ACL surgery was designated as the 'involved' leg, with the other knee being the 'uninvolved' leg. For healthy participants, their non-dominant leg was designated as their 'involved' leg. The sampling rate of the EMG and accelerometer was 1926 samples/sec and 148 samples/sec, respectively. Sensor noise was limited by shaving and cleaning each participant at the sensor locations prior to placement, and each sensor was then wrapped with medical tape to ensure stability over the duration of testing.

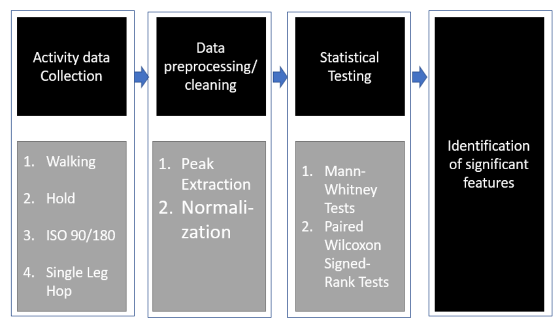
Figure 1. Sensor placement



III. Proposed Methods

[2] Our methodology is summarized in Figure 2. We will first describe the different activities performed, our data preprocessing and statistical analysis pipeline, and finally our feature importance analysis.

Figure 2. Our proposed framework



The following five activities were performed by each participant in order. Based on the recovery time for ACLR participants, some patients were not able to participate in hopping activities for preventative measures. For each activity, an upper-sided two sample Wilcoxon signed-rank test was performed for each of the 18 features comparing the healthy and ACLR participants. The Wilcoxon test was chosen because, as a non-parametric method, it does not require a normality assumption. The resulting p-value from this test will show if there is a significant difference between healthy and ACLR participants.

A. Walking Activity

The first activity measured was walking, where participants walked at a constant pace of three miles per hour on a treadmill for three minutes. This was done primarily as a warmup for the remaining activities but was also used for analysis to measure potential difference between the gait of healthy participants and patients.

The EMG and acceleration values were normalized for each participant to allow for consistent comparisons between trials. Then, using peaks in the acceleration data, each alternating stride was shifted in the time domain, so the peak force values approximately lined up for both the uninvolved and involved legs. Following the time adjustment for strides and normalization of metrics, the walking data were combined into two tables, one for each type of participant.

B. *ISO 90 & ISO 180 Activities*

Isokinetic testing was used to measure the strength of the involved leg versus the strength of the uninvolved leg. Isokinetic exercise occurs when limb movement velocity is held constant by a device. Participants conducted two tests while seated in the Biodex Multi-Joint System, one with each leg. The two tests, "ISO 90" and "ISO 180", differed in the strength of the resistance applied to each leg, where "ISO 90" offered less resistance than "ISO 180". The participants were instructed to perform 8 kicks per leg for each test.

The raw EMG data for each patient for the two isokinetic movements, 90 and 180, contained one peak for each kick the patient performed during the test. Participants were instructed to perform 8 kicks, but, due to participant error, 61.3% of the participant trials included 9 kicks. The peaks in the EMG data were isolated in Python using the "biosignalsnotebooks" library, and each peak was summarized using 18 features as previously done in a previous EMG study [10]. The 18 features are as follows: variance, root mean squared, integral, mean absolute value, log, wavelength, average amplitude change, difference absolute standard deviation value, zero-crossing, Willison amplitude, myopulse percentage rate, frequency ratio, mean power, total power, mean frequency, median frequency, peak frequency. The median of each feature was calculated for each participant's uninvolved and involved leg using all available peaks. The median was used because it is more resistant to outliers than an average in small sample sizes. Since the data for the participant's involved and uninvolved leg could not be treated as independent, the difference between the uninvolved and involved leg was found for each of the median features of each participant.

C. *Hold Activity*

The hold activity measured the muscle strength of the involved leg and uninvolved legs over a continuous period. Patients were seated in the Biodex Multi-Joint System and instructed to kick their leg at full force and hold for 30 seconds while the chair remained locked in place.

To measure the strength of the involved and uninvolved legs during the hold activity, the first derivative was taken of the EMG data to measure the fatigue rates. Next, the variance of both the EMG and accelerometer data was extracted. For the accelerometer data, the variance in the X, Y, and Z directions was extracted to determine if the leg was shaking. The average across the three directions was taken to compare uninvolved vs. involved legs and healthy vs. unhealthy patients. To measure speed, EMG was utilized to determine the time it took for subjects to reach their peak EMG value.

D. *Single Leg Hop Activity*

The single leg hop activity measured the horizontal distance a patient could jump and land on one leg. The patient used both legs to jump and landed on one leg. There were a total of 6 recorded jumps in which the patient landed on the involved leg and uninvolved leg which were recorded in an alternating manner. If the patient were to improperly stick the landing, the activity would be redone on that given leg.

The subject data was assessed taking into consideration the patient's involved and uninvolved leg. For each leg, the EMG data was extracted from each of the 3 jumps so that additional activity recorded by the sensors was removed. Patients' jumps were classified by the periods of significant increase in EMG values across the data collection period. This was accomplished by using the "biosignalsnotebooks" python notebook to detect EMG activation periods during activity peaks. The EMG values during muscle activation periods on a given leg were concatenated into a single vector for each patient. Feature extraction was then performed on each of these datasets and then merged into a dataset grouped by healthy/patient and involved/uninvolved legs. Averaging these peak feature values for each subject delivered the final feature values among the population groups.

E. *Predictive Modeling*

Using both EMG and acceleration data extracted from each patient for each activity, we propose to use a random forest algorithm to predict if a given segment of activity is being performed by the involved or uninvolved leg and healthy vs. ACL patients.

IV. RESULTS

A. *Walking Activity*

Out of the 20 walking features analyzed, four were found to have a statistically significant difference between healthy participants and ACL patients at a level of $\alpha=0.05$: the median and mean of acceleration in the Z direction, the median of acceleration in the X direction, and the mean difference between normalized EMG values of a participant's uninvolved and involved legs. These results are summarized in the table below.

Table 1. Comparing walking activity data between healthy ACL vs. patients

Category	Sensor	Feature	p-value
Force/Strength	EMG	Mean	0.58200
Force/Strength	EMG	Median	0.96970
Force/Strength	EMG	Variance	0.39960
Force/Strength	EMG	SSI	0.49570
Force/Strength	EMG	RMSE	0.43380
Speed	Acceleration - X	Mean	0.05091
Speed	Acceleration - X	Median	0.04784
Speed	Acceleration - X	Variance	0.29710
Speed	Acceleration - X	SSI	0.75190
Speed	Acceleration - X	RMSE	0.15790
Stability	Acceleration - Z	Mean	0.04591
Stability	Acceleration - Z	Median	0.01601
Stability	Acceleration - Z	Variance	0.38780
Stability	Acceleration - Z	SSI	0.28480
Stability	Acceleration - Z	RMSE	0.15790
Symmetry	EMG Differences between Legs	Mean	0.01655
Symmetry	EMG Differences between Legs	Median	0.09450
Symmetry	EMG Differences between Legs	Variance	0.62810
Symmetry	EMG Differences between Legs	SSI	0.41160
Symmetry	EMG Differences between Legs	RMSE	0.94070

As the four significant features found during the walking activity - the median and mean of acceleration in the Z direction, the median of acceleration in the X direction, and the mean difference between normalized EMG values of a participant's uninvolved and involved legs - appear to be the best predictors between healthy participants and patients.

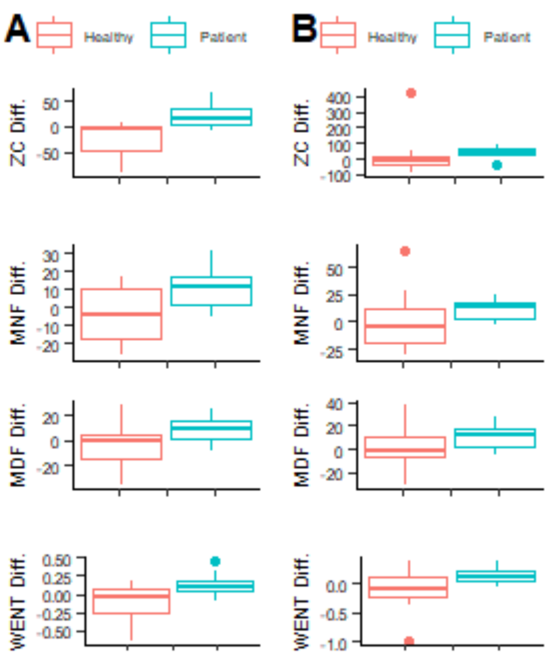
When developing a model to monitor the progress of a patient, these measures of speed, stability, and symmetry should be included. These features especially should be investigated in future studies, potentially with the addition of sensors on both the upper and lower half of patients' legs to measure the full range of motion of their gait.

B. ISO 90 & ISO 180 Activities

Zero crossing, median frequency, mean frequency, and wavelet energy all have the lowest p-values across both the isokinetic 90 and 180 movements. The complete results of the statistical tests are shown below.

Table 2. Difference between uninvolved and involved legs between healthy ACL vs. patients

Figure 3. Comparing healthy ACL vs. patients for iso180 (A) and iso90 (B) activities



Statistical testing revealed zero crossing (ZC), mean frequency (MNF), median frequency (MDF), and wavelet energy (WENT) to be the most relevant features for the isokinetic 90 and 180 movements. ZC was the most statistically significant feature across both exercises, as ZC was significant at the .05 and .005 significance level for the isokinetic 90 and 180 movements respectively. Based on our analysis, ZC, MNF, MDF, and WENT should be investigated further as potential reliable indicators of a patient's recovery from ACLR when analyzing EMG data from isokinetic activities.

C. Hold Activity

The p-values for the hold activity are shown in the table below. None of the statistical tests were significant at the α=.1 significance level, but the lowest p-value came from the variance of sensor acceleration in the Y direction.

Table 3. Significance of Hold Activity Features

Metric	p-value
EMG Variance	0.3750
RMSE	0.3750
Median	0.2324
Variance Acc X	0.6250
Variance Acc Y	0.1055
Variance Acc Z	0.3223
EMG 1st Derivative	0.6250

Following feature extraction and statistical analysis with the hold data, no features were found to be of any significance. Raw EMG data ultimately lacked sensitivity and led to no major findings. Therefore, EMG data from the hold activity was deemed to be a poor predictor of patient's recovery from ACLR.

D. Single Leg Hop Activity

The results are in the table below. Highlighted tests are significant at α=.05

Table 4. Single leg hop activity significance

Metric	H_P	Hinv_Huninv	Pinv_Puninv	Hinv_Pinv	Huninv_Puninv
RMS	0.0466160	0.7239320	0.8345316	0.1824224	0.1424668
IEMG	0.0291422	0.4799287	0.8345316	0.2301393	0.0455003
MAV	0.0370089	0.7910815	0.6761033	0.2301393	0.1095986
LOG	0.2388312	0.9292716	0.6761033	1.0000000	0.1424668
WL	0.0415780	0.6588433	0.8345316	0.1424668	0.1824224
ACC	0.1873283	0.9296365	1.0000000	0.3506479	0.4237108
DASDV	0.2401207	0.6588433	0.6761033	0.2861224	0.6891565
ZC	0.2214689	0.7910815	0.8345316	0.2301393	0.6891565
WAMP	1.0000000	0.6834580	0.1797125	0.3248721	0.3535932
MYOP	0.2038789	0.5364995	0.8345316	0.4237108	0.2861224
FR	0.6487567	0.8598192	0.6761033	0.5938029	1.0000000
MNP	0.0328746	0.6588433	0.8345316	0.1424668	0.0830364
TP	0.0058350	0.7239320	1.0000000	0.0830364	0.0455003
MNF	0.7553057	0.4267767	0.4033953	0.7897258	0.8939298
MDF	0.9808688	0.1447051	0.6761033	0.6888323	1.0000000
PKF	0.8667130	0.1850994	0.6761033	0.7894998	0.8939298
WENT	0.8291760	0.2509983	0.8345316	0.7897258	1.0000000

Root mean squared, integral, mean absolute value, wavelength, mean power, and total power were shown to be the most relevant for the single leg hop activity. These differences were significant between the healthy and patient groups in their entirety. However, no significant differences were found between healthy and patient groupings comparing involved and uninvolved legs. This suggests that the single leg hop activity is not an accurate representation of ACLR recovery. Furthermore, our data shows that there is a significant difference among all patients and an individual measure of performance.

Only six of the twelve ACLR patients were able to perform the activity during data collection due to the recency of their operation. This limitation was likely a contributing factor to the failure of significance of the activity as well as its low validity.

E. Predictive Modeling

Using leave one out cross validation (LOOCV) the classification model predicted the involved leg vs. uninvolved leg with an accuracy of 63% and an F1 score of 63% and accuracy of 63% and an F1 score of 58% when predicting healthy vs. unhealthy. Using Random Forest feature importance, it was found that the two most important features were left leg EMG and right leg EMG in both prediction tasks. These two features predictive importance shows that the activation of the muscles is more important to predicting ACL tears than the acceleration of the leg in a given direction.

Table 5. Feature Importance of Machine Learning Algorithm

	Involved vs. Uninvolved	Healthy vs. Unhealthy
Feature	**Importance Value**	**Importance Value**
Right Leg EMG	0.36	0.34
Left Leg EMG	0.33	0.29
Left Leg Acceleration X-direction	0.07	0.06
Left Leg Acceleration Y-direction	0.06	0.07
Right Leg Acceleration X-direction	0.06	0.05
Right Leg Acceleration Y-direction	0.05	0.1
Left Leg Acceleration Z-direction	0.04	0.03
Right Leg Acceleration Z-direction	0.03	0.06

V. Discussion & Conclusion

Though the results presented in our work are promising, few limitations still exist. The limited number of patients in our study likely contributed to the limited number of statistically significant results. The small sample size makes it difficult to generalize results and draw sustainable conclusions. In addition to having limited data, unequal class sizes also impact the ability to make generalizable claims across groups. Imbalance classes can lead to biased statistical models that favor certain groups. Future works should seek replications in a larger sample size and while balancing the number of subjects in each group (gender, age, months post-surgery, etc.). Additionally, participants ranged from being 2 to 8 months post-surgery. Differences in recovery time likely caused data discrepancies for the unhealthy patients, which would be exacerbated by the small sample size. External factors such as age, gender, strength, and dominant leg could have also resulted in skewed data. Although the researchers attempted to minimize noise through precise sensor placement and cleansing of the skin, noisy data still resulted due to motion artifact, cross-talk contamination, clipping, and physiological noise [11]. Another data collection inconsistency arose from the sensor attachment. Some subjects knocked the sensor and disturbed its placement, which could cause issues with data collection.

Our work is best interpreted as an initial exploration of how EMG data can be used to assess patient recovery. With the features identified, future researchers can build solutions that incorporate these findings to reduce the time, effort, and inaccuracy associated with assessing patient ACLR recovery. One such solution to be investigated is an at-home wearable EMG sensor capable of detecting patient recovery by leveraging the insights and framework from our paper. Another extension of our research could be in a clinical setting, where future researchers can work to develop an EMG solution to predict patient recovery that leverages our paper's proposed framework and the significant features identified.

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