Wearable Kneecap for Detecting Asymmetric Gait Patterns in ACL Reconstruction Recipients

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***Abstract* — The anterior cruciate ligament, or ACL, has always been a major problem for athletes and active people. In recent years, surgeons have adopted wide implementation of ACL Reconstruction (ACLR) as a tool to restore functionality and stability of the knee joint. The ACL reconstruction surgery has high success rate but the journey towards recovery after the surgery is long and strenuous. Detection and control of asymmetric walk patterns is one of the major issues in this stage. The potential of wearable three-axis Accelerometer based kneecap device is investigated in this paper in view of mitigation of above highlighted issues and also to achieve an optimum level recovery following surgery. Furthermore, we explore the surrounding aspects of ACL injury treatment and recovery, underscoring the benefits of modern technology in ameliorating lives for people recovering from ACL injuries.**

***Keywords*— Anterior cruciate Ligament Reconstruction (ACLR), asymmetry gait pattern, wearable technologies, Kneecap device, 3-axis Accelerometer sensor, recovery**

I. Introduction

ACL injuries constitute a major problem, especially in athletics and active people. Injuries commonly occur due to sudden intense movements like quick turns, twist or blows on the knees which create high pressure and damage the important anterior cruciate ligament (ACL) which stabilizes the knee joint as shown in figure 1. Due to the high rate of ACL injury repair, surgical reconstruction is increasingly used to restore knee joint stability and functionality.

The postoperative rehabilitation after ACL reconstruction is an important stage in the whole recovery process [1]. During this stage, a framework is laid for the eventual health state and living standards. The first major issue is asymmetrical gait pattern detection and management at this stage [2]. It is typical for the patients who have undergone an ACL reconstruction to initially experience a natural gait asymmetry while adjusting to their new 'artificial' knee. Approximately half of those undergoing ACLR surgery will eventually develop OA that could be caused by changed movement patterns resulting in peculiarities of the knee load [3,4]. The abnormalities in the stride can occur due to muscle inconsistencies, unconventional mechanics, pain, as well as discomfort that have not been completely eliminated. The recognition and treatment of such non-typical gait patterns is necessary for both current healing and avoiding future injuries [5].

Hence, the wearable kneecap device that comes with a 3-axis accelerometer is expected to provide the much-needed solution. The device has been developed for the treatment of gait pattern asymmetry on ACL patients. It collects, analyses and monitors a receiver's gait in real time by integrating sensory technology with Arduino IDE platform. Consequently, we examine the difficulties that patients undergoing anterior cruciate ligament replacement encounter, particularly in relation to the asymmetry of their stride gait pattern.

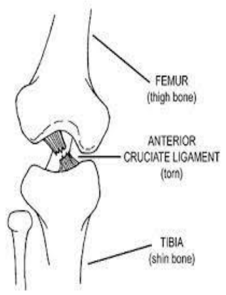

Fig. 1 ACL torn and wanted a Reconstruction

1.1 Major Contribution

The project's paramount contribution lies in the creation of a specialized wearable kneecap designed for real-time monitoring of gait patterns in ACL reconstruction recipients. This innovative device integrates seamlessly into rehabilitation programs, capturing data to enable the detection of subtle asymmetries between the reconstructed and unaffected limbs. Using advanced algorithms, the accompanying data analysis framework provides a novel method for recognizing and measuring gait changes. Beyond technological innovation, the project's relevance lies in its goal of giving medical professionals timely, actionable insights to tailor rehabilitation strategies and potentially facilitate early interventions, thereby enhancing the overall success of ACL reconstruction procedures and improving patient outcomes.

II. Related Study

New research approaches in ACL and gait analysis have been considered in recent studies on how to treat and assess subjects. In particular, there is increased attention to using assistive technologies in medicine with reference to the NanoStim project and a study by Sultan dealing with electrostimulation treatment for KOA (knee osteoarthritis) patients with the aid of wearable device [6]. Therefore, gait analysis is considered to be an essential method of quantifying body movements, mechanics, and muscle activity. Milic used Optogait whose data can be shown in real time using a software program, combined with side and back video analysis. The Optogait system was placed on a treadmill to observe the gait cycle parameters and provided information on movement asymmetries. This paper presented the iso-efficiency speeds (IES) approach for uphill walking and outlined the associated advantages of lower metabolic cost. The deterministic analysis although was equation driven gave concise conclusions comparable to expected outcomes drawn from existing literature [7].

Research [8] also proposed long-term gait asymmetries following operation which can be identified through wearable sensors and possibly create personalized rehabilitation plans that will minimize OA development [9]. Wearable sensor is a potential low-cost technology that can be used on daily basis gait analysis yielding information regarding kinematics and kinetics values. Besides, an exhaustive assessment per the literature would also comprise muscle activation pattern especially concerning the quadriceps muscles during ACLR rehabilitation due to acknowledged weaknesses and irregular neural control [8, 10, 11].

A gait analysis is more than a muscle study. It is essential in the comprehension of locomotion and ambulation, which provide early warnings of senile dementia and Alzheimer's disease [12]. Gait analysis also adds to the assessments of frailty, detection of specific aspects of mobility within various domains, tracking of activities, unusual behavioural patterns, and risk determinants [13, 14].

Video cameras, environment sensors, as well as small portable devices are widely used for data collection across different areas providing advantages like outdoor functions, insensitivity towards obscuration or luminance problems [15]. In general, all of these studies portray a multidisciplinary approach towards the comprehension and tackling of health problems, integrating modern technologies with the clinical perspective.

III. MATERIALS

An ESP32 and a 3-axis accelerometer are used to identify asymmetric gait patterns in patients undergoing ACL surgery.

A. 3-Axis Accelerometer

From figure 2, A 3-axis accelerometer, The MPU6050 sensor, which measures acceleration along the X, Y, and Z axes, is used in this case. By collecting motion data, it plays a crucial role in identifying patients who have undergone knee anterior cruciate ligament replacement surgery and who have uneven gaits.

B. ES32

In the wearable kneecap device, ESP32 (figure 3) acts as a master controller. This hardware records data from the 3-axis accelerometer in real time, and analyses it. Through this, the ESP32 helps the device identify and measure skewed gait patterns appropriately. Furthermore, it provides customizable algorithms and real-time feedback thus giving this device an extra advantage of being able to offer personalized rehabilitation and monitoring after ACL reconstruction surgery thereby improving postsurgical outcomes and patient care.

C. SD Card Module

The wearable kneecap device has an SD card module inside of it that stores data. This allows the accelerometer's three axes to collect relevant data on gait patterns, which the gadget may store. After then, these data can be obtained to assess the efficacy of the rehabilitation techniques.

D. Battery Shield

This wearable device uses as its reliable power source a 2600mAh lithium-ion battery located in the 18650-battery shield. It is an energy efficient shield that regulates and converts to the electricity required for operation with prolonged data retrieval processes. Its huge battery reserves power is vital to keep up with extended real-time analysis and surveillance during the gadget's operation.

IV. METHODS

A. Wearable Acquisition System

This study proposes the use of Inertial Measurement Units (IMU) such as the MPU 6050 as shown in figure 5, for motion biomechanics measurement by the Wearable Acquisition System [16]. The IMU's gyroscope and magnetometer sensors consist of accelerometers and gyroscopes with three axis (x, y, z) that gives important kinematic data about segment rotations [17]. The famous MPU-6050 that has an accuracy gives three 16-bit Analog-to-Digital converters that tracks both high and low speed movements (fast and slow). Flexibility on capturing different kinds of motion is provided by MPU-6050 with programmed ranges for gyroscope and accelerometer outputs [18,19].

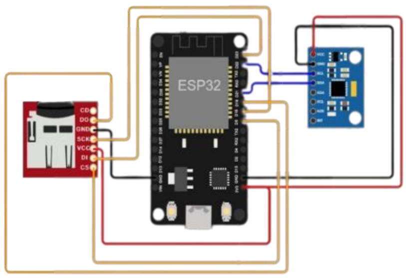

Fig. 4 Circuit Diagram of Wearable Acquisition System

From the figure 4, The architecture of the Wearable Acquisition System centres around the ESP32 Microcontroller Unit (MCU), chosen for its low cost and the availability of wireless communication protocols, including Wi-Fi and BLE. This MCU facilitates the collection of data from the MPU-6050 through the I2C bus, enabling efficient data transfer. The system comprises a Li-ion battery, an MCU, and the IMU sensor, with a voltage regulator integrated into the battery shield for stable power output. Using the ESP32, a localhost dynamic webserver is created. WebSocket Webserver is a technology that allows for real-time, full-duplex communication between a client and a server over a single, long-lived connection. Unlike traditional HTTP communication, which follows a request-response model, WebSocket enables bi-directional communication, making it ideal for applications requiring real-time updates.

The IMU is a Data Logger implemented using WebSocket Webserver technology. The system involves an ESP32 equipped with sensors for capturing data, such as accelerometer readings. The ESP32 is connected to a WIFI network and serves a web page through a WebSocket server. This web page displays real-time graphs of the sensor data using Chart.js library. Users can access this web page from a web browser to visualize the sensor readings dynamically. Additionally, users have the option to download the entire dataset in CSV format for further analysis. The project offers a convenient and efficient way to monitor and analyse sensor data remotely in real-time. Knee data is also offline stored for subsequent processing via an SD card module.

To ensure the Wearable Acquisition System is practical and user-friendly, the electronic components are assembled on a universal perforated board and housed in a protective cardboard case. This case is designed with features to stabilize and secure the system on a person's thigh, including gaps for clothing elastics. The ESP32 MCU, with its computational power, allows for high-frequency data acquisition, and a specific thread is programmed to collect IMU samples every 10 ms, aiming for a sampling frequency of 100 Hz. However, due to processing power sharing, the actual frequency ranges between 66–77 Hz, with an average time interval of 13 ms between collections.

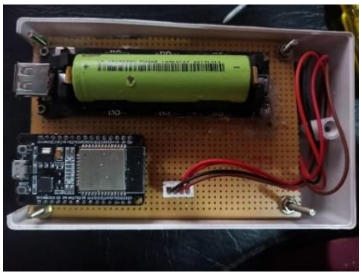

Fig. 5 Wearable Acquisition System

Along with the forward vectors, other aspects of the data capture include the time steps, forward acceleration, and magnitude vectors. These files are stored on an SD card for processing after an offline period, with wireless transmission being an option for later transfer. Adopted strategy guarantees smooth flow of information, which might contain a maximum of sixty samples in each second. The Wearable Acquisition System provides complete information on real-time biomechanics analysis of motion with possible usage in healthcare or recovery.

B. *Low Pass Filter Implementation*

Fig. 6 Implementation of the Low Pass Filter (LPS)

Figure 6 illustrates the usage of the Low Pass Filter (LPF) in the IMU, which is a crucial component that raises the motion data's precision. The main function of LPF is to cut off high frequency distortions or unessential variations thereby assuring the essential, smooth changes on recorded data.

LPF is essential in reducing noise artifact as well as jitter, which may occur during data acquisition processes like gait analysis and biomechanics. The LPF acts as an efficient filter that smooths random motions as well as rapid fluctuations and high-frequency components and thereby improves SNR and provides better representation of real motion dynamics within received signals.

These include the LPF with a cut-off frequency of 150 Hz and first order filter whose specific parameters will provide the right mixture of noise reduction combined with retaining of the relevant motion information. High-frequency attenuation begins at the cutoff frequency, and the rate of reduction is determined by the filter order.

***Algorithm 1**:*

Input

x	//Raw signal
y	//Filtered Signal
x[n]	*//Present Raw value*
y[n]	*//Present filtered value*
y[n-1]	//Previous value of y[n]
x[n-1]	//Previous value of x[n]

Output

y[n]=c1*y[n-1] + c2*x[n] + c2*x[n-1]

c1=Coefficient 1
c2=Coefficient 2

The implementation of constant coefficient difference equation in time domain of the above algorithm 1 is done using Python Environment, required certain libraries where the continuous transfer function and discrete transfer function is solved. Upon solving, the coefficients are c1=0.72848 and c2=0.13575.

C. *Motion Language Design*

Fig.7 Implementation of the Low Pass Filter (LFS)

The main goal is to create a clear language for motion biomechanics, defining meaningful parameters like forward acceleration, angle and magnitude vector. Carefully chosen parameters capture essential motion dynamics, with added attention to representing temporal aspects through well-considered gait cycles. The Motion Language Design establishes a crucial common framework, from figure 7 that the IMU enabling seamless real-time monitoring and offline analysis of data collected by the Wearable Acquisition System. The parameters are:

1) Forward Direction

Another type of signal is one that records a higher acceleration in parallel with that of the human sagittal plane. The search is made to know whether any three accelerations are in place. Forward-direction signal is represented by a higher energy signal at the A_x, A_y, A_z signals. FD = MAX (A_x, A_y, A_z) in the forward direction while testing of the IMU Unit. Here, the forward motion is represented by the z-axis [20].

2) Angles

The code converts the MPU-6050 IMU sensor raw accelerometer data into three meaningful orientation angles; namely, pitch, roll, and yaw. These angles are calculated using trig functions like atan2() which converts input accelerator reading data. Such angles give relevant information about where the sensor has been orientated in 3D context [21]. In this instance, as observed from an accelerometer axis, the forward direction angle is parallel to the x-axis.

3) Magnitude vector of the Acceleration

$$A_{res} = \sqrt{A_x^2 + A_y^2 + A_z^2},$$

Where A_{res} is the resultant acceleration, and A_x, A_y, A_z are accelerations in the accelerometer's local coordinate system. the acceleration magnitude vector A_{res}, also called magnitude of total acceleration, is computed to utilize the combined information from the three signals. Due to its invariance to device rotations, this vector has found extensive application [22].

4) Gait cycle

Millis () is used by the system to design an intermittent data collection period based on time intervals. A loop function compares times with the defined interval and hence guarantees data collection every 10 milliseconds.

D. Gait Analysis Study

1) Segmentation

The raw accelerometer data is organized in separate gait cycle segments. These segmentation points are normally created by strikes or toe-offs. The segmentation points separate each step and focus is placed on an individual stride.

2) Peak Detection

These are referred to as down-peaks where they represent specific phases of gait when the feet are put on the ground. High peaks where they represent specific phases of gait when the feet are put off. These significant points in the accelerometer data are identified and marked with signal processing technologies such as peak detection algorithms.

3) Feature Extraction

A signal that matches the human sagittal plane is a signal that records greater acceleration. A search is performed to see which of the three accelerations are present. This may include amplitude, duration, and shape characteristics of both high and down peaks. Statistical measures, such as mean, variance, and skewness, can be computed to quantify the properties of each peak.

4) Data Analysis

They analyse the extracted and segmented data over time, detecting any abnormalities/asymmetries in the gait cycle. Heel-strikes are integral part of gait analysis and the proposed motion language methodology enabled us to identify it. The detected heel-strikes, together with those extracted from the reference signal, were used to estimate stride times. The stride-time acquired was utilized to calculate gait symmetry, which is a crucial component in determining the degree of recovery. The following formula can be used to calculate symmetry [23,24].

$$SI = \frac{T_R - T_L}{\frac{1}{2}(T_R + T_L)} 100, \%$$

where T_R represents the average stride time for the right bottom, and T_L represents the average stride time for the left bottom. A lower absolute value of the harmony indicator (SI) indicates a more symmetric walk, while a negative value suggests that the left bottom is, on average, slower than the right, and a positive value indicates the contrary. This harmony measure considers only the average stride time for each bottom, providing invaluable insight into the harmony and coordination of the gait cycle, especially relevant in the context of rehabilitation evaluations following surgery.

V. RESULTS & DISCUSSION

a) Stride time: (Peak detection)

The analysis revealed valuable insights into the symmetry of walking patterns. Stride ties, calculated based on identified heel-strikes, enabled the computation of a symmetric index (SI) that quantified the gait regularity. So here the right leg (normal knee-figure 9) and Left leg (ACL knee-figure 8) data's will be collected separately. So the growing curve towards the peak is swing phase and the decline curve is Stance phase. Here the samples were taken from the both legs for the analysis.

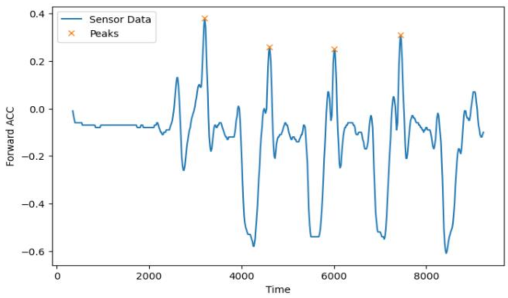

Fig. 8 Peak detection in ACL Leg

Peaks	Time Difference(ms)
Peak 1-2	1406
Peak 2-3	1399
Peak 3-4	1435

Table 1 – Peaks Gait cycle in ACL leg

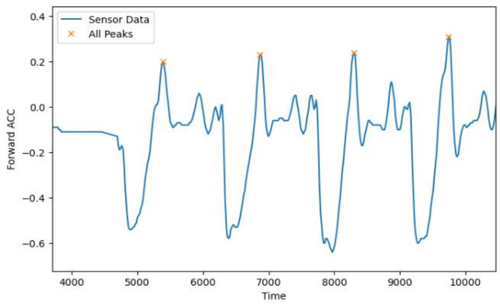

Fig.9 Peak detection in Normal Leg

Peaks	Time Difference(ms)
Peak 1-2	1475
Peak 2-3	1433
Peak 3-4	1443

Table 2 – Peaks gait cycle in Normal legs

From the tables 1,2, values of time difference from the both legs. We get a mean and standard deviation of ACL knee leg and normal leg as T_L=1413.33$\pm$15.58 ms and T_R =1450.33$\pm$17.91 ms respectively.

According to the symmetry formula, we get the Symmetry Index (SI) as +2.58, which is asymmetric and positive sign indicates that the right leg, on average, slower than the left leg (ACL knee leg was faster than normal leg).

b) Knee angles:

The analysis of knee flexion during the gait cycle handed fresh pivotal perceptivity into biomechanical aspects of ACLR cases. Knee flexion angles were tracked, contributing to a comprehensive understanding of common movements.

Figure 10 illustrates how the study focused on particular knee flexion and extension metrics at different stages of the gait cycle (1) maximum station phase knee flexion, (2) outside knee extension in terminal station phase, (3) maximum swing phase knee flexion, and (4) outside knee extension conterminous to heel strike in Figure 2. To grease comparisons across strides, the knee angle profile for each stride was regularized, defining a gait phase from 0 to 100. This normalization involved aligning the gait phase with 0 at the moment of original maximum knee extension (point 4), following maximum swing phase knee flexion (point 3). This normalization methodology is grounded on the observation that point 4 is conterminous to the original lading or heel strike in normal walking, furnishing a standardized frame for assessing knee common dynamics [25].

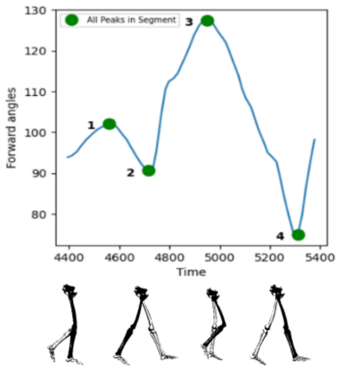

Fig.10 Phases of the knee angles

Figures 11 and 12 depict the plots of the normal knee and the ACL knee, respectively. Table 3 presents a comparison of the two legs with respect to the knee phases, including the mean and standard deviation.

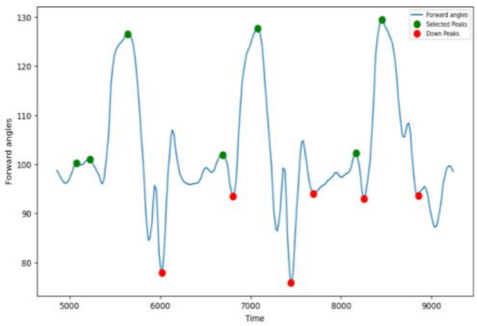

Fig.11Normal knee Angles

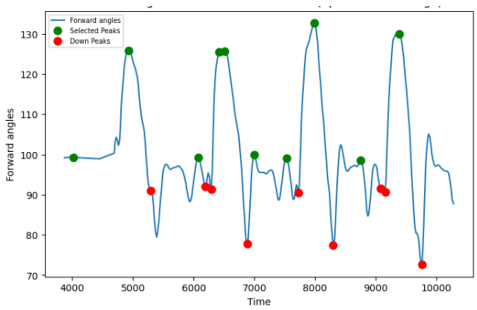

Fig.12 ACL knee angles

Phases	ACL knee Angles	Normal knee Angles
Maximum stance phase knee flexion	101.1±0.85	99.8±1
Maximum knee extension in terminal stance phase	92.88±0.97	91.68±0.98
Maximum swing phase knee flexion	128.11±1.15	128.51±3.12
Maximum knee extension adjacent to heel strike	75.09±3.48	75.35±2.1

Table 3 – Angles of ACL and Normal knee in the phases

VI. CONCLUSION

This is an established project that analyses gait technology and new age data processing methods. It is advantageous to employ the suggested motion language technique in conjunction with the MPU-6050 IMU sensor to properly acknowledge the primary gait events, which include heel strikes. The parameters are the stride time, gait symmetry index and knee flexing for a comprehensive study on the locomotion during walking.

It is possible to compare data across strides once normalization of knee angle profiles has been achieved thus providing an objective base for analysing the data. This, in essence, highlights a useful approach to ACLR which highlights a way forward post-ACL reconstruction.

Already, the proposed framework has demonstrated its viability, therefore it still leaves a lot of room for enhancements especially on machines intelligence. Future study must incorporate automatically identified patterns and extracted features in an attempt to enhance the analysis procedure. Future research may also concentrate on developing prediction models based on subtlety and real-time monitoring.

In short, this study forms an underlying basis that supports subsequent in-depth studies on individual items. Therefore, this study presents a method that can be employed to improve the process of rehabilitation and explain gait disorders.

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