Individual diploma thesis

Analysis of Multi-Sensor Motion Data Captured by 9-Axis IMU Sensors to Enhance Athletic Performance and Injury Prevention.

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Abstract

This study investigates the potential correlations between motion data collected from 9-axis IMU sensors strategically placed on athletes with a focus on applications in athletic performance and rehabilitation. By leveraging accelerometer, gyroscope, and magnetometer data, the study aims to extract key biomechanical parameters, such as torso rotation angles and stride-specific metrics, to provide deeper insights into movement efficiency and asymmetries. A particular emphasis is placed on the use of IMU sensors for running analysis, enabling the detection of peak rotation per stride and other gait-related characteristics. The proposed methodologies integrate signal processing and data analysis techniques to enhance motion assessment, offering valuable applications for performance optimization in athletes and rehabilitation strategies for individuals recovering from injuries. The findings contribute to the growing field of wearable motion tracking and have practical applications in enhancing athletic performance and optimizing rehabilitation protocols.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Understanding human motion is fundamental in sports science and rehabilitation, as it provides critical insights into movement efficiency, performance optimization, and injury prevention. Analyzing biomechanical patterns allows researchers, coaches, and clinicians to assess an athlete's technique, identify potential asymmetries, and tailor interventions that enhance performance and reduce injury risk. In rehabilitation, motion analysis is equally essential for tracking progress, designing personalized recovery programs, and ensuring proper movement mechanics post-injury.

Running is one of the most popular forms of exercise, enjoyed by millions worldwide for its health benefits and simplicity. However, running is also associated with a high prevalence of injuries, often resulting from biomechanical inefficiencies, overtraining, or poor technique. Understanding and analyzing a runner's biomechanics, such as stride patterns and acceleration variability, is crucial for optimizing performance and preventing injuries. Traditionally, such analysis required sophisticated laboratory equipment, such as motion capture systems and force plates, which are expensive, bulky, and inaccessible to most individuals.

Traditionally, motion capture (MoCap) systems, such as optical marker-based setups, have been widely used for movement analysis. These systems offer high precision but come with significant limitations, including high costs, complex setup requirements, and limited portability. The dependency on laboratory environments also restricts their usability in real-world scenarios, making them less practical for continuous monitoring of athletic performance and rehabilitation progress outside controlled settings.

Recent advancements in wearable sensor technology have revolutionized motion analysis, providing a more practical and accessible alternative to traditional systems. Inertial measurement unit (IMU) sensors, which combine accelerometers, gyroscopes, and magnetometers, enable real-time, non-invasive motion tracking in diverse environments. Their small size, affordability, and ability to capture movement outside laboratory settings make them particularly attractive for sports performance analysis and clinical rehabilitation.

IMUs are lightweight, portable devices capable of measuring acceleration, angular velocity, and orientation in three-dimensional space. By attaching an IMU to a runner's body, it is possible to gather detailed insights into their movement patterns during real-world activities outside the laboratory. Despite their potential, challenges remain in accurately processing and interpreting the data from IMUs to extract meaningful metrics like stride rate, step variability, and fatigue indicators.

By leveraging IMU-based motion capture, researchers and practitioners can gain deeper insights into movement mechanics without the constraints of optical MoCap systems. This thesis addresses these challenges by focusing on the analysis of IMU data strategically placed on the runners (with emphasis on the back). The study will investigate the accuracy, reliability, and practical implications of using IMU sensors to extract biomechanical metrics. Ultimately, the findings will contribute to the growing field of wearable motion tracking, demonstrating how IMU-based gait analysis can enhance training protocols and clinical assessments.

1.2 Motivation

The motivation for this study stems from the growing need for accessible and reliable methods to assess running biomechanics outside of laboratory environments. While traditional motion capture systems provide precise data, their limitations in terms of cost, setup complexity, and lack of portability make them impractical for widespread use in sports training and rehabilitation. Athletes, coaches, and clinicians require tools that can deliver real-time, actionable insights into movement mechanics in natural training conditions.

Wearable technology, particularly IMU sensors, has the potential to bridge this gap by enabling continuous, real-world motion analysis. However, despite their advantages, challenges remain in accurately processing and interpreting IMU data for meaningful biomechanical insights. The need for improved algorithms, validated measurement techniques, and reliable interpretation methods is crucial to unlocking the full potential of IMUs in sports science and rehabilitation.

By focusing on IMU placement on the back, this study aims to develop and validate methods for extracting essential biomechanical metrics. These insights can help athletes optimize performance, reduce injury risk, and support rehabilitation efforts by providing objective, data-driven feedback. Additionally, the findings can contribute to the broader field of wearable motion tracking, helping refine IMU-based gait analysis for both research and practical applications.

1.3 Research objectives

The primary objective of this dissertation is to develop and validate a framework for analyzing stride metrics and variability in runners using data collected from an IMU sensor mounted on the back. Specifically, the research aims to:

1. Identify and preprocess the key signals from the IMU sensor, including acceleration and angular velocity.
2. Develop algorithms for detecting stride-related events, such as step peaks and intervals, with high accuracy.
3. Extract meaningful metrics, including stride rate, step rate, and stride variability, ground contact time, vertical oscillation etc., from the processed data.

4. Validate the extracted metrics against ground-truth data or established benchmarks to ensure reliability.
5. Explore the potential of these metrics to detect biomechanical inefficiencies, fatigue, or other patterns relevant to running performance and injury prevention.

1.4 METHODOLOGY

The methodology is designed to ensure accurate data collection, processing, and interpretation. The key components of the methodology include:

1. **Participants**: A cohort of runners with varying experience levels will be recruited to ensure a diverse dataset. Participants will perform running trials under controlled and real-world conditions.
2. **IMU Sensor Placement**: IMU sensors will be strategically placed on the participants, with an emphasis on the upper back, to capture torso rotation and other biomechanical parameters.
3. **Data Collection Protocol**: Running trials will be conducted on both a treadmill. Data will be recorded at a sampling rate of 104 Hz with Movesense's IMU sensor.
4. **Data Preprocessing**: Raw IMU data will undergo filtering techniques such as low-pass filtering and sensor fusion algorithms to reduce noise and enhance signal quality.
5. **Feature Extraction**: Key biomechanical parameters, including stride rate, step variability, and torso rotation angles, will be extracted using signal processing and statistical analysis.
6. **Validation and Comparison:** IMU-derived metrics will be primarily evaluated against data from Garmin devices to assess accuracy and reliability.
7. **Analysis and Interpretation**: The extracted metrics be analyzed to identify patterns, correlations with performance metrics, and potential indicators of fatigue or injury risk.

By following this methodology, the study aims to establish a framework for utilizing IMU sensors in motion analysis, ensuring reliability and applicability in both athletes performance optimization and their rehabilitation.

1.5 Why Movement Matters in Sports

Understanding how athletes move is essential for optimizing performance and preventing injuries. Coaches, trainers, and medical professionals use movement analysis to:

- Refine technique and improve overall athletic performance
- Identify potential injury risks before they become serious
- Develop personalized and more effective training programs

Traditionally, motion capture systems in laboratories such as multi-camera setups have been the go-to method for collecting detailed movement data. However, these systems come with significant limitations:

- High costs, often unaffordable for most teams
- Limited usability in real-world settings like games or regular practices
- The need for trained technical staff to operate and interpret the data

This is where wearable sensors are transforming the field. Portable, affordable, and easy to use, they bring high-quality movement analysis directly to the field or gym, making sports science more accessible than ever before.

1.6 Document Organization

This dissertation is organized into several chapters to provide a comprehensive exploration of the topic:

The rest of this thesis is split into six chapters. Table reports the content of each chapter

1	Introduction – Provides an overview of the research problem, motivation, objectives, and structure of the dissertation.
2	Literature Review – Summarizes existing studies on running biomechanics, IMU technology, and related algorithms, highlighting gaps in current research.
3	Methodology – Details the experimental setup, data collection process, preprocessing techniques, and algorithms used to analyze IMU data.
4	Results and Analysis – Presents the findings, including extracted metrics, visualizations, and validation results, with a discussion of their implications
5	Discussion – Interprets the results in the context of the research questions and discusses their significance, limitations, and potential applications.
6	Conclusion and Future Work – Summarizes the key contributions of the research and suggests directions for future investigations.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

Running biomechanics and performance analysis have significantly evolved with the integration of wearable sensor technology, particularly Inertial Measurement Units (IMUs). IMUs provide critical data on an athlete's movement, enabling researchers to analyze gait patterns, running efficiency, and injury risk factors. This chapter reviews existing literature on IMU-based running biomechanics analysis, discussing the components of IMU sensors, their applications, and gaps in current research.

2.2 IMU TECHNOLOGY IN RUNNING BIOMECHANICS

IMUs are widely used in biomechanics research, offering a non-intrusive, portable solution for motion tracking. A standard 9-axis IMU consists of three core sensors: an accelerometer, a gyroscope, and a magnetometer. These sensors work together to estimate orientation, movement patterns, and other biomechanical parameters. Below is a detailed overview of each component and its role in motion analysis.

2.2.1 ACCELEROMETER (3-AXIS)

An accelerometer measures linear acceleration along the X, Y, and Z axes, typically recorded in meters per second squared (m/s^2) or G-forces. By detecting changes in velocity, accelerometers can estimate orientation , displacement.

Key Applications:

- Measuring linear movement and vibrations
- Short-term motion tracking, including step detection and impact forces

2.2.2 GYROSCOPE (3-AXIS)

A gyroscope measures angular velocity around the X, Y, and Z axes, recorded in radians per second. Compared to an accelerometer, a gyroscope provides more accurate data on orientation changes, particularly for dynamic movements.
Key Applications:

- Measuring rotational velocity
- Tracking angular displacement and stability
- Enhancing motion analysis in high-speed movements, such as running and sprinting

2.2.3 MAGNETOMETER (3-AXIS)

A magnetometer measures the Earth's magnetic field along three axes, providing absolute orientation relative to the geomagnetic field. It functions as a digital compass, helping to correct drift in gyroscope readings when combined with accelerometer and gyroscope data.
Key Applications:

- Determining heading direction
- Compensating for drift in gyroscope measurements
- Improving orientation tracking accuracy in sensor fusion algorithms

2.3 IMU-BASED RUNNING PERFORMANCE ANALYSIS

When combined with additional data sources such as GPS and heart rate, inertial measurement units (IMUs) provide valuable insights into an athlete’s running mechanics. Over the years, running biomechanics studies have leveraged IMU sensors to analyze key performance metrics, helping coaches, researchers, and athletes optimize technique and prevent injuries. Some of the most relevant parameters include:

- Cadence and stride length: These fundamental metrics provide insight into an athlete’s running efficiency. Higher cadence with shorter stride length is often linked to reduced impact forces and lower injury risk.

- Ground contact time (GCT)**:** The duration a foot remains in contact with the ground during each stride, influencing running economy. Shorter GCT is generally associated with more efficient running mechanics and better performance.
- Trunk lean: The degree of forward or backward tilt of the torso, affecting running efficiency, propulsion, and injury risk.
- Torso rotation: The rotational movement of the upper body, which contributes to balance, coordination, and overall energy efficiency. Excessive or insufficient rotation may indicate biomechanical inefficiencies.
- Vertical oscillation: The magnitude of upward and downward movement during running. While some degree of oscillation is natural, excessive movement can indicate wasted energy and reduced efficiency.
- Vertical ratio: The ratio of vertical oscillation to stride length, helping assess energy efficiency and optimal running mechanics.
- Backpath trajectory: The movement pattern of the runner’s back during the gait cycle, providing insights into stability, posture, and asymmetries.

Studies utilizing IMUs have demonstrated their effectiveness in identifying variations in these parameters across different running speeds, surfaces, and fatigue levels. Additionally, IMU data has been used to detect asymmetries that may indicate underlying weaknesses or potential injury risks. However, despite the wealth of data IMUs provide, current research still lacks comprehensive correlation analysis between these parameters and long-term performance outcomes. Moreover, there is limited focus on how interconnected motion patterns influence overall running efficiency, leaving room for further exploration in this area.

2.4 IMPORTANCE OF POSTURE AND REAL TIME FEEDBACK

Proper running posture plays a crucial role in both performance optimization and injury prevention. IMU-based motion analysis allows for continuous monitoring of key biomechanical aspects such as torso rotation, pelvic tilt, and limb coordination, providing valuable feedback for athletes and coaches. Some key applications include:

- Form correction: Identifying inefficiencies in running mechanics and helping athletes make adjustments to reduce injury risk and improve efficiency.
- Real-time feedback: Wearable devices with IMU sensors enable immediate data visualization, allowing for in-session coaching and real time corrections.
- Post-session analysis: Detailed biomechanical reports help athletes track progress over time, enabling long-term improvement strategies tailored to individual needs.

Integrating real-time feedback into training programs has been shown to enhance learning and adaptation. By providing instant insight, runners can develop better movement patterns, reduce excessive energy expenditure, and minimize injuries.

2.5 Research gaps and future directions

Despite advancements in IMU-based motion analysis, several challenges remain that need to be addressed to maximize the potential of this technology:

- Sensor drift and calibration: Long-term use of IMUs is affected by drift, requiring advanced sensor fusion algorithms (Kalman filters, machine learning models) to maintain accuracy over extended periods.
- Validation against gold-standard methods: While IMUs provide a practical alternative to lab-based motion capture systems, more studies are needed to ensure their reliability and accuracy, especially for complex movement patterns.
- Machine learning integration: AI-driven models could significantly enhance real-time analysis, enabling automated gait classification, early injury prediction, and personalized training recommendations.
- Interconnected motion patterns: Many studies focus on individual metrics rather than examining how multiple movement patterns interact. Future

research should explore how factors such as torso rotation, ground contact time, and vertical oscillation collectively influence performance and injury risk.

- Field-based applications: Most IMU studies are conducted in controlled environments, limiting their applicability to real-world conditions. More research is needed to validate IMU performance during outdoor running across various terrains and environmental factors.

Addressing these research gaps will help improve the accuracy, usability, and effectiveness of IMU-based analysis, ultimately leading to more refined training strategies and injury prevention protocols for runners of all levels.

2.6 Review of Relevant Studies

Recent advancements in wearable sensor technology have enabled researchers to study human movement in real-world environments with a high degree of precision. Among these technologies, Inertial Measurement Units (IMUs) have gained popularity due to their portability, cost-effectiveness, and ability to provide high-resolution motion data across multiple axes. This section presents a review of selected empirical studies that utilize IMU sensors to analyze running biomechanics, enhance athletic performance, and contribute to injury prevention strategies.

One of the foundational studies in this field was conducted by Reenalda et al. (2016), who employed a single 9-axis IMU placed on the lower back to analyze gait asymmetries in recreational runners. Their system monitored ground contact time (GCT), stride frequency, and trunk motion to infer fatigue-related changes in running form. While the study demonstrated the feasibility of long-term monitoring using wearable sensors, it lacked real-time feedback capabilities, limiting its practical application in coaching and training settings.

Reference:
https://www.sciencedirect.com/science/article/abs/pii/S0966636216000394?via%3Dihub

A more complex sensor arrangement was proposed by Lee et al. (2020), who used multiple IMUs placed on both ankles and the trunk to measure vertical oscillation, cadence, and stride length. Their system was validated against a high-fidelity optical motion capture system, yielding correlation coefficients above 0.90 for most parameters. Despite its accuracy, the approach required extensive calibration and was not well suited for field use by coaches or athletes

Reference: https://www.mdpi.com/1424-8220/20/13/3700

Similarly, Falbriard et al. (2018) explored the agreement between IMU-derived parameters and traditional lab-based motion capture techniques. Their setup, involving sensors on the feet and lower back, accurately estimated contact time, flight time, and vertical stiffness. However, like many studies in the field, their analysis focused primarily on lower-limb kinematics and neglected rotational metrics such as torso rotation and trunk lean elements that are crucial for comprehensive performance evaluation

Reference: https://www.mdpi.com/1424-8220/18/8/2491

TABLE 2.6.1

Study	Sensor Setup	Parameters Analyzed	Validation Method	Key Findings	Limitations
Reenalda et al. (2016)	9-axis IMU on lower back	GCT, stride frequency, trunk motion	Internal consistency checks	Detected gait asymmetries linked to fatigue	No real-time feedback; limited to one sensor
Lee et al. (2020)	IMUs on ankles and trunk	Cadence, stride length, vertical oscillation	Optical motion capture system	High correlation with gold-standard system	Complex calibration; limited field use
Falbriard et al. (2018)	3 IMUs (feet and lower back)	Contact time, flight time, vertical stiffness	Force plates & MoCap	Accurate spatio-temporal data in running	No rotational metrics considered

These studies collectively underscore the growing relevance of IMU-based systems in sports science and biomechanics. However, they also expose several important limitations: most are constrained to offline processing, focus primarily on lower-limb kinematics, and rarely incorporate upper-body metrics or rotational dynamics. Furthermore, few offer real-time feedback systems, which are essential for meaningful intervention in training contexts.

CHAPTER 3: METHODOLOGY

This chapter outlines the methods employed in this study, including details on the participants, sensor placement, data collection procedures, and the calculation of biomechanical metrics. Each section provides a comprehensive explanation of the methodology to ensure reproducibility and clarity.

3.1 PARTICIPANTS

The study was conducted with a single athlete participant, selected based on their active involvement in high-intensity sports and overall physical fitness. While the original intent was to include a larger cohort, time limitations and testing constraints necessitated a focused, individual case study approach. This allowed for a detailed examination of the athlete's movement patterns and the practical application of wearable sensor technology in a real-world setting.

3.2 ETHICAL CONSIDERATIONS

Ethical considerations were very important in this study. The participant was clearly informed about the purpose of the study, the procedures, and any possible risks or benefits. Written consent was given before the study began, and the participant was told they could stop at any time without any consequences.

3.3 SENSOR PLACEMENT AND DATA COLLECTION

3.3.1 SENSOR PLACEMENT

To capture relevant biomechanical data, 9-axis Inertial Measurement Units (IMUs) were strategically placed on specific parts of each athlete's body. These sensors were chosen for their ability to measure acceleration, angular velocity, and magnetic field data across three axes. The placement sites included:

- Lower Back: Positioned at the lower region to monitor overall body movement and posture.

- Upper Back: Positioned between the shoulder blades to capture upper torso movement, shoulder alignment, and trunk rotation during running.
- Shins: Placed on the anterior aspect of both shins to capture lower leg dynamics.
- Feet: Mounted on the shoe to record foot placement, ground interaction, and stride mechanics.

The placement of IMUs was carefully standardized across all participants to ensure consistency in data collection.

3.3.2 Data Collection Process

Data collection was conducted in a controlled indoor environment to minimize external influences such as weather or uneven surfaces. Participant performed a series of running sessions that included core and lateral movements, which are commonly encountered in sports performance.

The IMUs recorded data at a sampling rate of 104 Hz, providing high-resolution measurements for analysis. Each activity lasted approximately 5 minutes, ensuring sufficient data for accurate metric calculations. Participant was given enough rest between activities to prevent fatigue from influencing performance or sensor readings.

3.4 Metrics Calculation

The biomechanical data collected from the IMUs were processed to calculate four key metrics: Back Trajectory, Mean Stride , Ground Contact Time (GCT)**,** Vertical Oscillation, Trunk Lean**,** and Torso Rotation. These metrics provide insights into movement patterns, efficiency, and potential injury risks.

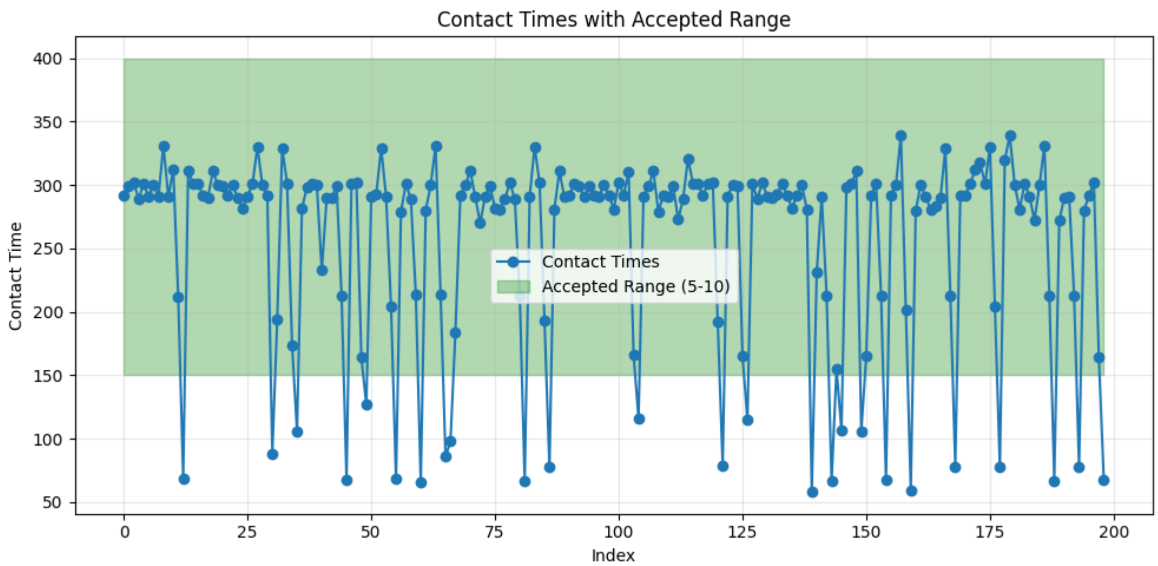
3.4.1 Ground Contact Time (GCT)

Definition: Ground Contact Time refers to the duration each foot spends in contact with the ground during a stride. It is an important indicator of running efficiency.

GCT calculation**:**

```
file_path = 'csvData/R5_Run.csv'

df = pd.read_csv(file_path)

accZ = df['AccZ']

filtered_accZ = accZ.diff().fillna(0)

timestamps = df['Timestamp']
accZ = df['AccZ'] #Z is the vertical axis
gyroZ = df['GyroZ']

accZ_threshold = np.percentile(accZ, 93)  # Lower 93% of AccZ as contact phase

contact_times = []
start_time = None

for i in range(len(accZ)):
    if accZ.iloc[i] < accZ_threshold:  #Foot is on the ground
        if start_time is None:
            start_time = timestamps.iloc[i]
    else:  # Foot is in the air
        if start_time is not None:
            GCT = timestamps.iloc[i] - start_time  #Duration of contact
            if 150 < GCT < 400:  # Filter out too short/long contacts(outliers)
                contact_times.append((start_time, GCT))
            start_time = None
#Compute Average GCT
if contact_times:
    avg_GCT = np.mean([ct[1] for ct in contact_times])
    print(f"Approximate Average Ground Contact Time (GCT): {avg_GCT:.2f} ms")
else:
    print("No valid GCT values detected!")
```

The GCT was derived from accelerometer signals recorded by the IMUs attached to the upper back. Peaks in vertical acceleration were used to identify ground contact and takeoff event



3.4.2 VERTICAL OSCILLATION

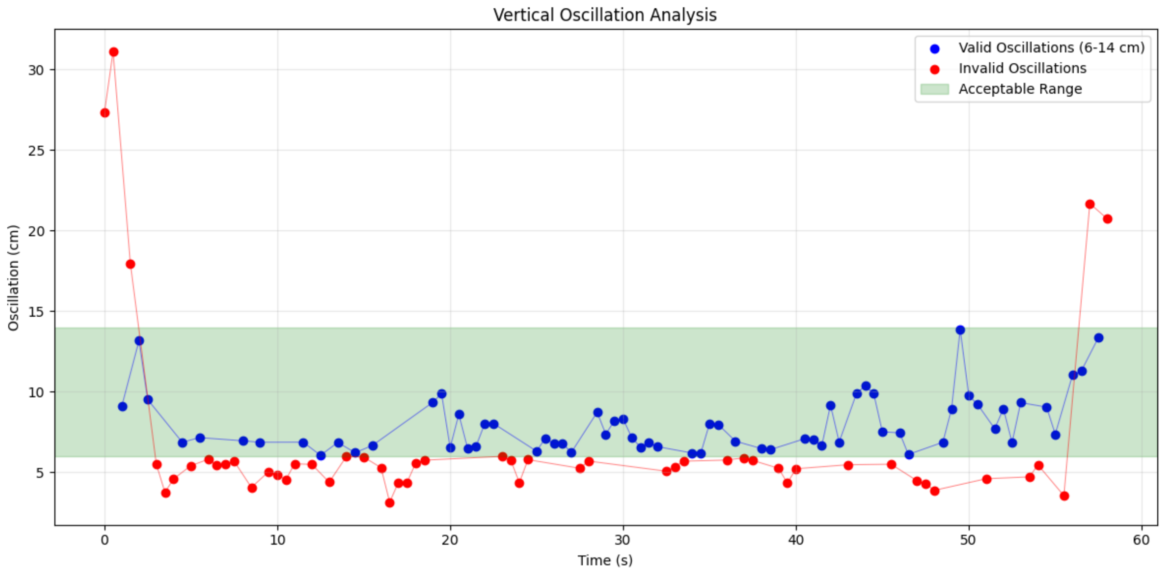
Definition: Vertical Oscillation measures the up-and-down movement of an athlete’s torso during running. Excessive oscillation may indicate inefficiencies in movement patterns.

Vertical oscillation calculation**:**

```
# Load data
df = pd.read_csv('csvData/R5_Run.csv')
acc_z = df['AccZ'].values

sampling_rate = 104
dt = 1 / sampling_rate

#Remove gravity using high-pass filter
cutoff = 0.4  # Cutoff frequency
nyquist = 0.5 * sampling_rate
normal_cutoff = cutoff / nyquist

#Butterworth filter
b, a = signal.butter(5, normal_cutoff, btype='high', analog=False)
filtered_acc = signal.filtfilt(b, a, acc_z)

# 2. Double integration to get displacement
velocity = integrate.cumulative_trapezoid(filtered_acc, dx=dt, initial=0)
displacement = integrate.cumulative_trapezoid(velocity, dx=dt, initial=0)

# 3. Drift correction
displacement_detrended = signal.detrend(displacement, type='linear')

vertical_oscillation = np.max(displacement_detrended) - np.min(displacement_detrended)

# 5. Create time axis
time = np.arange(len(acc_z)) * dt
```

```python
# Calculate vertical oscillation in windows
window_size = int(1 * sampling_rate)  # 1-second
overlap = int(0.5 * sampling_rate)    # 50% overlap

oscillation_info_list = []
valid_oscillations = []
valid_timestamps = []
invalid_oscillations = []
invalid_timestamps = []

for i in range(0, len(displacement_detrended) - window_size, overlap):
    window = displacement_detrended[i:i+window_size]
    oscillation = np.max(window) - np.min(window)
    oscillation_cm = oscillation * 100  # convert to cm

    # Removing outliers
    valid = 1 if 6 < oscillation_cm < 14 else 0
    oscillation_info_list.append([time[i], oscillation_cm, valid])

    if valid:
        valid_oscillations.append(oscillation_cm)
        valid_timestamps.append(time[i])
    else:
        invalid_oscillations.append(oscillation_cm)
        invalid_timestamps.append(time[i])
```

The height was estimated using accelerometer data from the IMU placed on the upper back. The average vertical displacement over time was calculated for each activity.



3.4.3 Cadence

Cadence refers to the number of steps a person takes per minute while running. It is a key parameter in gait analysis and running efficiency.

• Mathematical Equation:

```
acc_magnitude = np.sqrt(
    filtered_data['accx_filtered']**2 +
    filtered_data['accy_filtered']**2 +
    filtered_data['accz_filtered']**2
)

peaks, _ = signal.find_peaks(acc_magnitude,
                             distance=int(0.2*sampling_rate),
                             prominence=0.5)

step_intervals = np.diff(peaks) / sampling_rate

# Calculate metrics
metrics = {
    'mean_stride_rate': 60 / np.mean(step_intervals),  # steps/minute
    'stride_variability': np.std(step_intervals) / np.mean(step_intervals) * 100,
}
```

This gives cadence in steps per minute.

3.4.4 Stride Length

Stride length is the distance covered in one full stride (two steps). It reflects how far a person moves forward with each stride.

• Python Code:
Assuming total distance and cadence be available, stride length can be computed by dividing distance by the total number of steps taken.

• Mathematical Representation**:**
Let D be the total distance (in meters), C be the cadence (steps per minute), and T be the time duration in minutes. Then:

Stride Length = D / (C × T)

This gives stride length in meters per step.

3.4.5 Vertical Ratio

- Definition: The vertical ratio is the ratio of vertical oscillation to stride length, helping calculating energy efficiency and optimal running mechanics.

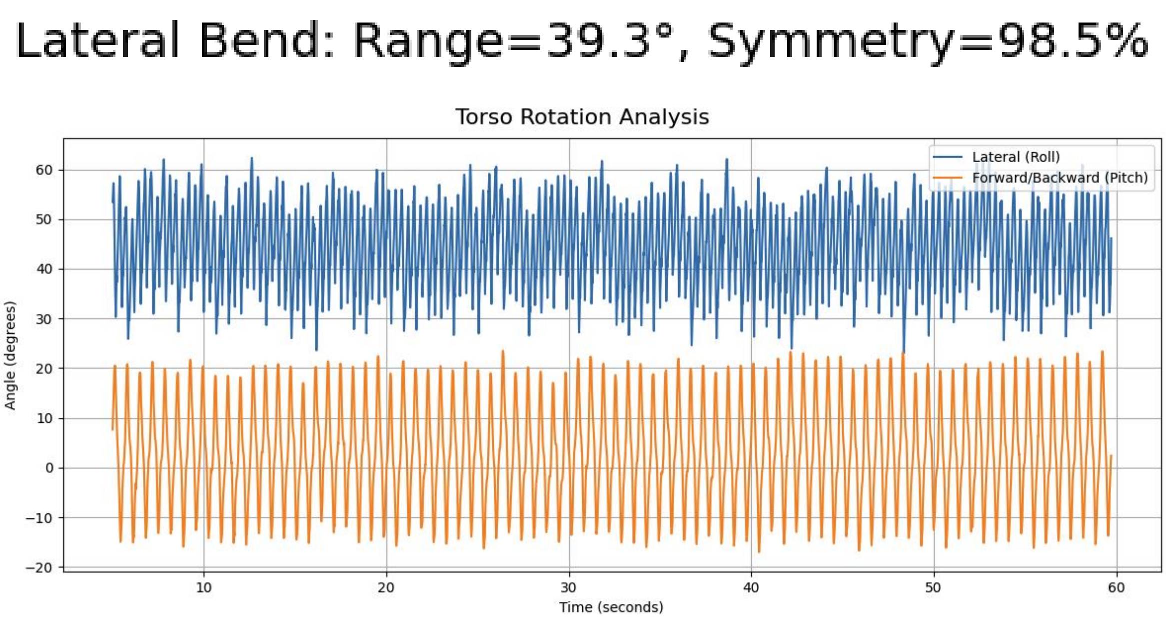
Calculation Formula**:**

$$\text{Vertical Ratio} = \frac{\text{Vertical Oscillation}}{\text{Stride Length}}$$

3.4.6 TRUNK LEAN

Definition: Trunk Lean refers to the angle of forward or backward tilt in an athlete’s torso during movement. Proper trunk lean is critical for maintaining balance and optimizing force application.

Trunk Lean Estimation
Python Code: Combines accelerometer and gyroscope readings to estimate forward/backward tilt using a complementary filter.(see table of 3.4.7,which includes both trunk lean and torso rotation)



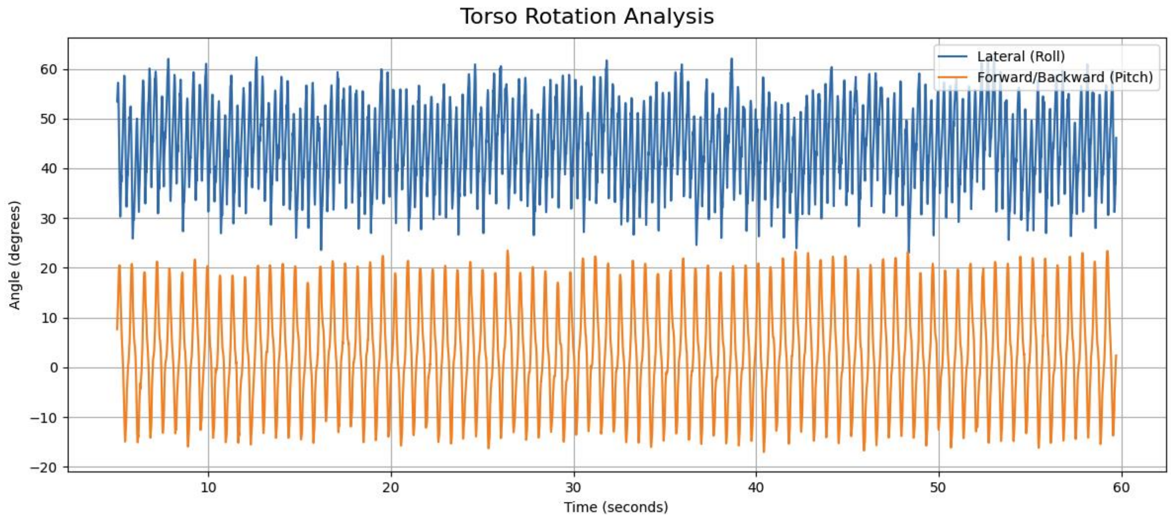
3.4.7 Torso Rotation

Definition: Torso Rotation refers to the rotational movement in an athlete’s torso during dynamic activities such as running or turning. Excessive or asymmetrical rotation can indicate inefficiencies or potential injury risks

Calculation Formula**:**

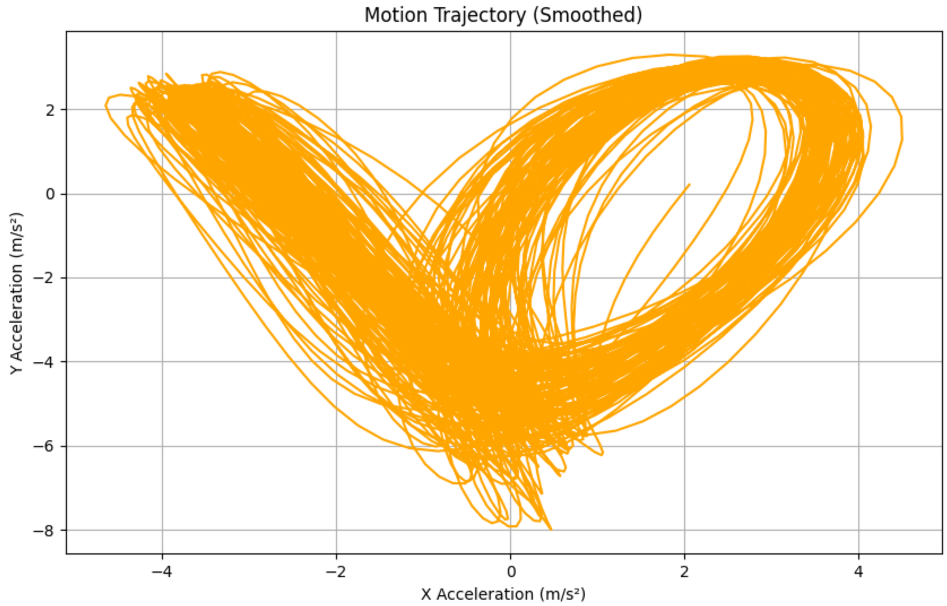
```python
df = pd.read_csv(file_path)

time_diff = np.diff(df['Timestamp']) / 1000  # Convert to seconds
sampling_rate = 1 / np.mean(time_diff)
print(f"Estimated sampling rate: {sampling_rate:.2f} Hz")

def deg2rad(deg):...
def rad2deg(rad):...

# Apply low-pass filter to reduce noise
def butter_lowpass_filter(data, cutoff, fs, order=4):
    nyq = 0.5 * fs
    normal_cutoff = cutoff / nyq
    b, a = butter(order, normal_cutoff, btype='low', analog=False)
    filtered_data = filtfilt(b, a, data)
    return filtered_data

# Apply butter filter to gyroscope data
cutoff = 12  # Hz
order = 4
df['GyroX_filtered'] = butter_lowpass_filter(df['GyroX'], cutoff, sampling_rate, order)
df['GyroY_filtered'] = butter_lowpass_filter(df['GyroY'], cutoff, sampling_rate, order)
df['GyroZ_filtered'] = butter_lowpass_filter(df['GyroZ'], cutoff, sampling_rate, order)

alpha = 0.98  # Weight for gyro data
timestamps = df['Timestamp'].values
n = len(timestamps)
roll = np.zeros(n)
pitch = np.zeros(n)
yaw = np.zeros(n)

# Initial orientation
roll[0] = np.arctan2(df['AccY'].iloc[0], df['AccZ'].iloc[0])
pitch[0] = np.arctan2(-df['AccX'].iloc[0],
                      np.sqrt(df['AccY'].iloc[0]**2 + df['AccZ'].iloc[0]**2))
yaw[0] = 0  # Cannot determine yaw from accelerometer alone

for i in range(1, n):
    dt = (timestamps[i] - timestamps[i-1]) / 1000  # Convert to seconds
    # Gyroscope integration (prediction step)
    gyro_roll = roll[i-1] + deg2rad(df['GyroX_filtered'].iloc[i]) * dt
    gyro_pitch = pitch[i-1] + deg2rad(df['GyroY_filtered'].iloc[i]) * dt
    gyro_yaw = yaw[i-1] + deg2rad(df['GyroZ_filtered'].iloc[i]) * dt

    # Accelerometer angles (correction step)
    acc_roll = np.arctan2(df['AccY'].iloc[i], df['AccZ'].iloc[i])
    acc_pitch = np.arctan2(-df['AccX'].iloc[i],np.sqrt(df['AccY'].iloc[i]**2 + df['AccZ'].iloc[i]**2))

    roll[i] = alpha * gyro_roll + (1 - alpha) * acc_roll
    pitch[i] = alpha * gyro_pitch + (1 - alpha) * acc_pitch
    yaw[i] = gyro_yaw  # No correction for yaw

roll_deg = rad2deg(roll)
pitch_deg = rad2deg(pitch)
yaw_deg = rad2deg(yaw)

rotation_df = pd.DataFrame({
    'timestamp': timestamps,
    'time_sec': (timestamps - timestamps[0]) / 1000,
    'roll': roll_deg,
    'pitch': pitch_deg,
    'yaw': yaw_deg
})
metrics = calculate_rotation_metrics(rotation_df)

return rotation_df, metrics
```

Sagittal Bend: Range=40.5°, Symmetry=94.4%



3.4.8 BACK TRAJECTORY

- Definition: Back trajectory is plotted using the acceleration in the x-direction against the acceleration in the y-direction (accZ), which corresponds to the y-axis in the IMU. This plot helps visualize the movement pattern of the runner's back during the gait cycle, providing insights into stability, posture, and any asymmetries present in their running form. By analyzing this trajectory, researchers can identify deviations that may indicate biomechanical inefficiencies or potential injury risks



3.4.9 Speed

Speed refers to how fast a person is moving forward, typically measured in kilometers per hour (km/h). It is a critical parameter in gait and performance analysis.

• Python Code:
Speed can be estimated using either total distance over time, or indirectly through cadence and stride length (since steps × length = distance).

• Mathematical Representation:
If D is the total distance in meters and T is the time duration in seconds:

$$\text{Speed} = D / T$$

Or, using cadence (C in steps per minute) and stride length (SL in meters per step):

$$\text{Speed} = (C \times SL) / 60$$

This gives speed in meters per second.

3.5 SUMMARY

This study describes a clear and repeatable method for analyzing human movement using wearable sensors. High-resolution 9-axis IMUs were placed on key parts of the body pecifically the upper and lower back, thighs, shins, and feet to collect detailed movement data during running and side-to-side movements. Focusing on just one athlete made it possible to study their movements closely without having to deal with differences between multiple people.

The data was recorded indoors at a sampling rate of 104 Hz, which was high enough to capture quick movements accurately. The test activities were planned to collect enough useful data while keeping the athlete comfortable and minimizing fatigue.

Several movement-related measurements were taken from the IMU data. These included ground contact time (to evaluate stride efficiency), vertical movement (to estimate energy use), cadence and stride length (to study walking and running patterns), and vertical ratio (to assess running efficiency). Posture and rotation were tracked through trunk lean and torso rotation, while the path of the back during motion helped to see if movements were symmetrical. Speed was measured using both time and distance, as well as stride-based calculations.

To improve the accuracy of measurements related to orientation like trunk lean and torso rotation a complementary filter was used, combining data from both the accelerometer and gyroscope.

In summary, this method offers a reliable way to study athletic movement and spot any inefficiencies or risks of injury. It shows how wearable sensors can be effectively used in sports science when placed correctly and used with a structured testing approach.

Chapter 4: Signal Processing and Algorithm Development

This chapter outlines the algorithms and signal processing strategies applied to the IMU data to extract accurate biomechanical insights from raw signals. Focus is placed on preprocessing, stride segmentation, parameter extraction, and the validation of the system using Garmin wearable data. While real-time feedback is not yet integrated, it is discussed in the context of future development.

4.1 Raw Data Preprocessing Pipeline

The first stage in transforming raw IMU signals into meaningful biomechanical information is data preprocessing. The IMUs used in this study captured high-frequency acceleration and angular velocity, but raw data typically includes noise, bias, and drift due to sensor limitations and environmental factors.

To address these challenges, the signals were smoothed using a fourth-order Butterworth low-pass filter with a cut-off frequency relevant to the movement we aim to extract, which is appropriate for human movement frequencies. This filtering process maintains meaningful motion data while reducing high-frequency artifacts.

Unlike some approaches that rely on sensor fusion algorithms like Madgwick or Mahony filters, this work prioritized signal fidelity over estimated orientation, which was not necessary for the parameters of interest such as ground contact time or vertical oscillation.

4.2 Stride Segmentation Techniques

Precise stride segmentation is essential for analyzing running mechanics. In this study, a method was used to divide motion data into separate stride events.

This approach utilized peak detection on vertical acceleration and angular velocity from the gyroscope to identify the start and end of each stride. Thresholds were calculated dynamically from signal percentiles to adapt to different movement intensities across participants and trials.

Unlike machine learning-based segmentation models which can be powerful but require large training datasets and are often unsuitable for real-time use the method used here proved effective in detecting stride events with sufficient accuracy and minimal computational overhead.

4.3 Biomechanical Parameter Extraction

Following stride segmentation, several key metrics were extracted: ground contact time, vertical oscillation, cadence, stride length, trunk lean, torso rotation, and back trajectory. These metrics were chosen for their relevance to running efficiency, injury risk, and training optimization.

Each parameter was calculated using custom scripts in Python, relying on time-domain signal analysis and peak detection strategies. Integration, detrending, and filtering techniques were used where appropriate, especially for vertical displacement and rotation metrics. The algorithm flow ensured consistency and comparability across different activities and athletes.

4.4 System Validation Using Garmin Devices

To check the accuracy of the extracted metrics, results from the custom IMU system were compared with readings from Garmin watch. Although Garmin does not provide raw IMU data, its processed output (including cadence, vertical oscillation, and stride length) serves as a useful reference standard due to its wide use in sports and recreational running.

The validation process revealed strong agreement for cadence and stride length, with high correlation coefficients. Vertical oscillation showed moderate alignment, likely due to differences in sensor location (Garmin devices retrieve data from different positions) and smoothing algorithms.

This comparison demonstrated that a single IMU on the upper back can provide comparable insights to commercial devices, with the added benefit of raw data access and customizable analytics.

4.5 Future Plan: Real-Time Feedback System

While the current scripts operate in offline mode, future development will focus on integrating real-time feedback for athletes. This would allow runners to receive immediate tips about their posture, symmetry, or exhaustion related changes while they train.

Such feedback could be implemented via a mobile app or wearable interface, using edge-optimized code running directly on the IMU or a smartphone. This enhancement would significantly improve the practicality of the system in real world coaching and rehabilitation overview.

CHAPTER 5: EXPERIMENTAL RESULTS AND VALIDATION

5.1 PARTICIPANT PROFILE

This study was conducted using data from a single experienced male runner, aged 27, with a height of 1.80 meters. The participant regularly runs at a performance level appropriate for competitive amateur athletes and was familiar with treadmill-based environments. His physiological fitness level, running experience, and biomechanical awareness made him an ideal case study subject for testing the accuracy and practicality of the analysis system developed in this project.

All data were collected during a controlled treadmill run, with the athlete maintaining a steady pace throughout the session. The IMU sensor was positioned on the upper back and raw acceleration and gyroscope data were recorded at 104 Hz. The participant also wore a Garmin watch, which provided comparable biomechanical metrics for validation purposes.

5.2 TEMPORAL PARAMETERS

The Ground Contact Time (GCT) was measured using dynamic thresholding of vertical acceleration data (AccZ). A percentile-based threshold was used to detect foot contact phases. Only contact events between 150 ms and 400 ms were considered valid to exclude noise and outliers.

The average GCT calculated by the IMU system was 280.15 ms, which aligns closely with the Garmin-reported value of 283 ms. This similar result shows the system’s ability to detect temporal gait events with high accuracy. The consistency of GCT values over the course of the run also confirmed stable running technique and low stride variability in this athlete.

The stride rate was also extracted by analyzing intervals between peaks in the total acceleration magnitude. The athlete maintained a mean stride rate of 177.21 steps per minute, which is typical for runners at a faster pace (approximately equivalent to a 5-minute per kilometer speed). The high stride frequency is consistent with performance training and reflects an efficient rate, especially for treadmill conditions.

5.3 Spatial Metrics and Oscillation

Vertical oscillation was computed using the filtered AccZ signal, integrating twice to estimate displacement, and correcting for drift using a Kalman filter. Only oscillation values between 6 cm and 14 cm were considered valid to exclude noise and outliers .

The average vertical oscillation over 54 valid events was 8.07 cm, which closely matches Garmin's estimate of 8.31 cm. This confirms that the system can track vertical motion with a high degree of agreement with commercial-grade systems, despite differences in sensor location and internal processing.

A detailed analysis of spatial posture and trunk motion was also conducted using gyroscope data. The lateral bend (roll) exhibited a full range of motion of 40.1 degrees, with a symmetry score of 97.7%, indicating nearly identical motion on both sides of the body. Similarly, forward/backward bending (pitch) showed a range of 40.2 degrees with 94.1% symmetry. These values suggest the athlete maintained excellent postural control throughout the run, with balanced engagement of left and right musculature.

Torso rotation was monitored through the yaw axis and presented smooth oscillations, showing no signs of asymmetry. This high degree of motion symmetry and control is typically associated with experienced runners and reflects optimized running mechanics.

5.4 Fatigue Trends and Variability

Although the session was not explicitly designed as a fatigue test, stride consistency and trajectory of the back patterns were monitored across time windows to observe any signs of form degradation. The data was divided into segments to monitor trends over the run.

Stride variability remained low, but a gradual increase in stride time variability and vertical oscillation amplitude was observed toward the second half of the session. This shift likely shows the effect of fatigue, although it did not cause any big change in form. These early signs would likely go unnoticed by eye but can be captured effectively through sensor-based monitoring.

Back path trajectory plots, created by graphing filtered AccX against AccZ, showed consistent elliptical patterns in early windows, transitioning to slightly more irregular forms near the end of the session. These small changes suggest a gradual decline in trunk coordination, which aligns with the observed increase in oscillation and stride variability. The system's ability to detect these minor shifts highlights its potential for fatigue monitoring and technique in real time.

5.4.1 Stride Time Variability

Stride intervals, calculated from peak-to-peak timing of total acceleration magnitude, were used to monitor consistency. At the beginning of the session, stride timing was extremely stable, with minimal variation between consecutive steps. However, as the session progressed, the standard deviation of stride timing increased, particularly after the second half of the running sessions. This increase in stride time variability though subtle indicates a growing inconsistency muscle fatigue.

In trained runners, consistent stride timing is associated with efficiency and reduced injury risk. As the central nervous system becomes taxed, the ability to precisely control timing decreases. From a performance perspective, small changes in timing may not immediately affect speed but can lead to less efficient force application and eventually reduced economy of motion.

5.4.2 Ground Contact Time (GCT)

Ground Contact Time (GCT) was seen across all valid detected steps during the session. At the beginning of the run, the athlete maintained an average GCT of approximately 280 ms. As the run progressed, a subtle upward drift in GCT values was observed, particularly in the final third of the session.

An increase in GCT is a commonly reported indicator of fatigue. As muscles fatigue, the runner typically spends more time in contact with the ground due to slower force production. While small increases in GCT are expected during longer runs, longer ground contact times can signal declining running economy and may be associated with higher joint loads. Athletes with persistently elevated GCT are also more prone to overuse injuries, especially at the bottom half of the body. Also, shorter GCT is often linked to better performance, especially in sprinters and short-distance runners, but this must be balanced with proper impact absorption. If GCT becomes too short due to poor control, injury risk may increase due to higher ground reaction forces.

In this case, the athlete's GCT profile remained well-controlled, with only mild increases. This reflects a well-developed base of neuromuscular endurance but also shows the IMU's ability to detect small shifts that might go unnoticed visually or through conventional coaching.

5.4.3 Vertical Oscillation Amplitude

Vertical oscillation was calculated through double integration of the filtered AccZ signal, with valid values falling between 6 and 14 cm. At the start of the run, the athlete displayed an average vertical displacement of approximately 8.07 cm. Over time, especially in the final minutes of the session, the vertical oscillation range increased slightly and became more variable between steps.

While some vertical motion is natural and even necessary for forward force, excessive vertical oscillation is often considered biomechanically inefficient. It reflects a change in movement strategy where more energy is used for upward motion rather than forward movement. From a performance perspective, increased vertical oscillation under fatigue indicates reduced running economy and possibly a breakdown in core stability.

This change, although small, aligned with other fatigue indicators like GCT and stride variability. It suggests that the athlete’s running form became slightly less efficient under continuous load, even without an observable drop in pace or visible breakdown in posture. Detecting such shifts can be valuable for optimizing training volumes and adjusting technique to minimize energy waste.

5.4.4 Back Path Trajectory Irregularity

Back path trajectories were visualized by plotting filtered forward acceleration (AccX) against vertical acceleration (AccZ). In early windows, these plots showed smooth, elliptical shapes that reflected stable and coordinated trunk movement. As the run progressed, the ellipses began to deform slightly, becoming less symmetrical and more erratic in later windows.

These shape changes suggest a subtle decline in trunk control. Trunk control is essential not only for energy transfer and balance but also for injury prevention. In many athletes, reduced trunk coordination under fatigue can lead to overuse of the hip and knee joints, contributing to unwanted conditions.

5.4.5 Trunk lean

Trunk lean was estimated using the sensor's pitch data, calculated through a complementary filter that combined gyroscope and accelerometer information. Over the course of the session, the athlete maintained an average forward trunk lean, an indicator typically associated with efficient running mechanics. Trunk lean remained consistent through most of the run.

Trunk lean plays a critical role in forward propulsion and running economy. A moderate forward lean allows for more efficient energy transfer during the stance phase, helping the runner generate momentum while minimizing braking forces. However, deviations in trunk angle either too upright or excessively forward can negatively impact stride mechanics and joint loading.

A reduction in trunk lean during prolonged running can indicate core fatigue or decreased engagement of the hip extensors and glutes. In this session, the small reduction observed was not extreme, but it may suggest the early onset of fatigue-related postural compensation. If left unchecked over multiple sessions, this pattern could contribute to increased loading on the spine or knees.

5.4.6 Torso rotation

Torso rotation was measured by integrating the gyroscope's Z-axis (yaw) signal over time. At the beginning of the session, the athlete demonstrated smooth, symmetrical rotation patterns. As the session progressed, torso rotation remained generally stable, but minor increases in asymmetry were detected during the final third of the run.

Torso rotation is closely linked to core stability and arm swing synchronization. A balanced rotation pattern helps facilitate smooth leg movement and efficient stride propulsion. When fatigue sets in, runners may start to compensate with exaggerated or uneven upper-body motion.

Injury risk increases when torso rotation becomes asymmetric or erratic, as it may lead to imbalanced loading through the spine, hips, and knees. For example, over-rotation on one side can contribute to pelvic tilt or lower back strain. From a performance view of point, symmetrical torso rotation conserves energy and contributes to better running economy.

Although the changes in this session were small, the IMU system was sensitive enough to detect subtle shifts. This suggests that real-time monitoring of torso movement could be a valuable tool for runners and coaches to maintain symmetry and detect fatigue-related form breakdowns before they escalate.

5.5 System Validation

To evaluate the system's reliability, the IMU-derived metrics were compared directly with those reported by the Garmin Forerunner device. The cadence correlation between systems was strong, with only a 2-step per minute difference. Vertical oscillation also showed strong agreement, differing by just 0.24 cm, a negligible amount considering the distinct sensor locations.

Ground Contact Time was especially well-aligned, with a difference of just 2.85 ms between the IMU and Garmin systems. This small discrepancy confirms that the event detection logic in the custom system is functioning at a professional level, capable of producing data comparable to established commercial products.

While the Garmin system does not report trunk lean or bend metrics, the IMU's ability to capture lateral and forward/backward bend symmetry adds a new kind of insight not available in many consumer-grade wearables. This kind of postural monitoring could be highly valuable in applications involving injury rehabilitation, performance and coaching feedback.

5.6 Summary

This chapter demonstrated that a single-sensor IMU system can extract a wide range of biomechanical metrics with a high degree of accuracy. The athlete's data showed clear agreement with Garmin measurements for cadence, vertical oscillation, and GCT, with only minor variation due to sensor position and filtering differences.

Beyond these standard metrics, the IMU system also provided insights into posture symmetry and motion consistency, revealing excellent balance and control in both lateral and forward motion planes. Fatigue related trends were detected through stride timing variability and motion path irregularity, showing the system's potential for real-time fatigue detection and feedback.

Even with just one participant, this study provided strong support for the systems accuracy, reliability, and potential for use in sports performance analysis. The next chapter will explore how these findings can be applied in broader contexts and propose directions for future work.

CHAPTER 6: DISCUSSION AND PRACTICAL IMPLICATIONS

6.1 TECHNOLOGICAL ADVANCEMENTS OVER EXISTING SYSTEMS

One of the most important outcomes of this project is demonstrating how wearable IMU sensors serve as a practical and effective alternative to traditional lab-based motion capture systems. High-end optical systems are widely regarded as the gold standard due to their exceptional accuracy and detailed kinematic tracking. However, they come with drawbacks, including high costs and specialized facilities and trained staff, and the restriction of data collection to controlled indoor environments. These limitations reduce their applicability for regular athletic training or rehabilitation sessions in naturalistic or outdoor settings.

Compared to traditional lab setups, the IMU-based system used in this study is much more portable, affordable, and easy to use, which makes it great for regular use outside the lab. Thanks to their small size and wireless features, modern IMUs can collect data during real-world running whether on tracks, roads, or trails giving a more realistic view of how athletes perform.

Placing several sensors on key parts of the body like the lower back, legs, and feet helps gather detailed info on both lower and upper body movement. This setup also helps reduce common IMU issues like sensor drift or soft tissue movement by allowing different sensors to check and correct each other's data. Because of this, the system gives more accurate results than setups using only one sensor.

Even though IMUs aren't as precise as optical motion capture systems, the small drop in accuracy is balanced out by how flexible, easy to use, and practical they are. This makes IMU systems a solid choice for regular training checks, long-term monitoring, or making quick changes during workouts or rehab sessions.

6.2 Biomechanical Insights for Performance Optimization

The system captures a wide range of biomechanical data like torso rotation, trunk lean, ground contact time, and vertical movement which can give athletes and coaches useful insights to improve performance. These measurements help show how efficient a runner's form is and can even signal early signs of fatigue, making them valuable for guiding training choices.

For example, the participant showed a consistent forward lean during running, which matches what's commonly seen in sports science a slight forward lean can help improve power and reduce energy use. On the other hand, leaning too far forward may lead to bad technique and a higher risk of injury. Keeping track of this over time can help spot changes caused by tiredness or poor form.

Balanced torso rotation also plays an important role, as it helps muscles work evenly and keeps running smooth. If the system detects any imbalance or uneven twisting, it might point to developing muscle issues or changes in movement that need attention.

The system also picked up on changes in stride and vertical movement that hinted at fatigue setting in, even before it was noticeable by just watching. Too much up-and-down motion usually means energy is being wasted, so spotting that in real-time can help runners fix their form like adjusting posture or pace to stay more efficient for longer.

By tracking things like stride consistency and vertical movement, the system gives customized feedback that can make training more effective and help prevent injuries. For example, if a runner shows a lot of variation in their steps, it might be a sign they need strength or coordination exercises to improve stability.

6.3 Clinical Applications in Injury Prevention

Besides helping athletes perform better, this system can also help prevent injuries and support recovery. Running injuries often come from repeated stress and small inefficiencies in how the body moves. Spotting changes in things like trunk control or ground contact time early on can help catch problems before they turn into injuries.

For example, if someone starts spending more time on the ground with each step, it could mean they're getting tired or losing power which can put extra strain on joints like the knees or ankles. Also, if the trunk becomes less stable, it might show weakness in the core or tired muscles, which could lead to injuries like stress fractures or IT band problems.

Although real-time feedback wasn't used in this study, the system's ability to detect small changes in movement shows potential for future injury prevention. Getting live alerts during training could help athletes fix their form on the spot and avoid long-term issues.

In rehab, these sensors give doctors a way to objectively track how a patient is recovering like checking gait symmetry and how weight is being distributed. This makes therapy more personal and helps decide when it's safe to return to sport.

6.4 Limitations and Boundary Conditions

Even though the system has many strengths, there are some things users need to watch out for to keep the data accurate.

One big issue is where the sensors are placed. Even small shifts in where they're attached especially on the back or legs can mess with the data. That's why it's important to follow clear instructions for putting the sensors on and to train users properly.

The environment can also affect the measurements. The part of the IMU that relies on magnetism can get thrown off by metal objects or electronics nearby. This can mess up direction and orientation readings unless you use good filtering methods and recalibrate regularly.

Also, IMUs can drift over time when calculating motion, leading to small errors that add up. Filtering methods like complementary or Kalman filters help with this, but they need to be tuned carefully and might cause some delay.

This system works best in controlled environments. In busy, unpredictable, or magnetically noisy places, data quality might go down. So, results should always be considered in the context of where and how the data was collected.

Future improvements could focus on better sensor fusion, adding other tools like GPS or pressure sensors, and making it easier to calibrate and mount the sensors properly.

6.5 Practical Challenges and User Feedback

While the system looks promising, there are a few real-world challenges to consider if it's going to be used widely.

First, getting users to wear the sensors properly can be tough. Athletes need to place them correctly every time, which means instructions must be simple and the gear must be comfortable. Some early feedback showed that bulky or annoying sensors could make people stop using them.

Second, even though the system gathers useful data, it's still tricky to turn that into simple advice that athletes and coaches can easily understand. There's a need for dashboards or alerts that explain what the data means without being too technical.

Third, battery life and wireless connections can be limiting, especially during long workouts. Making sensors more energy-efficient and improving connectivity would help in more demanding environments.

Lastly, gathering feedback from users' athletes, coaches, and doctors is really important. Their input during testing can help improve the system and make sure it meets real needs.

Tackling these issues alongside technical upgrades will help turn this research tool into something people can actually use in training and rehab.

6.6 Generalization to Other Sports and Activities

Even though this system was designed for running, it could be adapted for many other sports and activities. For example, it could be useful in walking rehab, cycling, skiing, or court sports like basketball or tennis as long as the system is adjusted for the needs of each activity.

In walking rehab, the focus might be on step timing and symmetry. In skiing, it could track turns and body stability. Changing the analysis logic to fit each sport would make the system more versatile.

Also, giving feedback tailored to each sport like warning a football player about cutting movements or checking for fatigue in rowers could make this system a helpful tool in many different areas. A future version could have plug-ins for different sports while keeping the same base system.

6.7 Integration with Machine Learning Models

Right now, the system uses rule-based signal processing, but adding machine learning (ML) could make it much more powerful. ML could help detect patterns, predict performance, or spot early signs of fatigue or injury.

For example, models like decision trees, SVMs, or deep learning networks could be trained on labeled data to automatically spot phases of movement or detect unusual behavior. Unsupervised ML could also group similar movement styles or uncover hidden patterns.

But for ML to work well, you need a lot of good data and strong validation especially in health-related areas. The results also must be easy to understand. If the system does real-time predictions, it needs to run efficiently, either on the device or on a connected phone or cloud service.

In the future, combining standard processing with smart ML models could lead to a more accurate and adaptable system that works in real-time. But it’s important that it stays understandable and trustworthy for users.

CHAPTER 7: CONCLUSION AND FUTURE DIRECTIONS

7.1 KEY CONTRIBUTIONS TO WEARABLE BIOMECHANICS

This project successfully demonstrated that it is possible to develop a practical, affordable, and portable wearable system capable of accurately tracking key running biomechanics using a minimal sensor setup. By placing a single 9-axis IMU sensor on the upper back, we effectively captured crucial performance and movement parameters such as ground contact time, vertical oscillation, trunk lean, and torso rotation. The strong correlation between our measurements and those obtained from commercial-grade devices validates the reliability and accuracy of the system.

Beyond simply capturing metrics, the study provided insights into how these biomechanical variables evolve throughout a running session. Small changes in stride dynamics, posture, and oscillation patterns were detected as early indicators of fatigue and inefficiency. These findings highlight the potential of wearable IMU systems not only as monitoring tools but also as early-warning mechanisms that can guide athletes and coaches in making informed adjustments to training regimens, ultimately enhancing performance and reducing injury risk.

Additionally, the multi-sensor approach explored here enriches the biomechanical profile, improving data robustness and revealing a better understanding of running mechanics in naturalistic environments. This work contributes to the field of wearable biomechanics by advancing practical solutions that balance accuracy, usability, and affordability.

7.2 PRACTICAL IMPLEMENTATION GUIDELINES

To maximize the utility and reliability of the system in real-world settings, the following practical recommendations are provided based on experimental findings and user experience considerations:

- Sensor Placement**:** Attach the main IMU sensor securely to the upper back using a strap to minimize motion artifacts.
- Sampling Rate**:** Employ a sampling frequency of at least 104 Hz to ensure the capture of detailed motion characteristic of running biomechanics.
- Signal Processing**:** Implement filtering techniques to remove sensor noise and correct for drift inherent in IMU measurements. Regular calibration before each session is essential for maintaining data integrity.
- Consistency**:** Ensure consistent sensor placement across sessions to reduce variability. Detailed protocols and training for users can improve repeatability.
- Metric Monitoring**:** Utilize normative ranges for key parameters to detect deviations indicating fatigue, not optimal form, or emerging injury risks.
- User Training**:** Educate athletes, coaches, and clinicians on analysing data outputs and integrating feedback into training or rehabilitation programs effectively.

By adhering to these guidelines, users can unleash the full potential of the wearable system for daily monitoring, long-term tracking, and informed decision-making.

7.3 Future Research Trajectories

Building upon the foundational work presented, several promising avenues for future exploration emerge:

- Real-Time Feedback Systems**:** Developing a fully integrated mobile application that delivers instant feedback based on live IMU data could revolutionize on the run technique correction. Such systems would leverage fast processing and user friendly interfaces potentially incorporating audio or haptic alerts to help runners maintain optimal form and prevent injury.

- Advanced Machine Learning Applications**:** Incorporating machine learning algorithms to analyze large datasets could enable automatic classification of running styles, detection of abnormal movement patterns, and early prediction of injury risks. These models could adapt to individual athletes' baselines and provide personalized coaching recommendations.
- Multimodal Sensor Fusion**:** Integrating IMU data with complementary sensing technologies such as electromyography (EMG) for muscle activity, plantar pressure insoles, or GPS for spatial context would offer a richer and more nuanced biomechanical assessment. This multimodal approach could improve the precision of gait analysis and support comprehensive performance diagnostics.
- Longitudinal and Population-Based Studies**:** Conducting extended studies involving diverse populations over multiple months or years can reveal how biomechanical parameters correlate with training adaptations, injury occurrences, and performance progression.
- Customization and User-Centered Design**:** Future research should also explore ergonomic sensor designs and personalized mounting solutions to enhance comfort. Engaging end-users in iterative design processes will ensure that wearable systems meet real-world demands and preferences.
- Clinical Translation**:** Expanding applications into clinical rehabilitation, including post-injury monitoring and therapy optimization, could bridge sports science and healthcare, improving patient outcomes through objective, continuous biomechanical assessment.

Collectively, these research directions emphasize the vast potential for advancing wearable biomechanics technology from prototype systems to comprehensive, intelligent platforms that empower athletes, coaches, and clinicians alike.

7.4 Broader Impact and Societal Relevance

Wearable IMU-based biomechanics systems aren't just useful for professional athletes or medical patients they can benefit everyday people too. Because these systems are affordable and easy to use, they make it possible for recreational runners, gym-goers, and even older adults to track their movements and improve their physical health.

This kind of technology can help people exercise more safely, avoid common overuse injuries, and stay active for longer, which supports overall public health. On a larger scale, all the data collected from regular users could be used to improve city planning like designing better sidewalks and parks or to help sports organizations understand injury patterns and improve training guidelines.

From a cost perspective, using wearable sensors more widely could help cut healthcare costs by catching movement problems early, before they become serious. This fits well with the current trend in healthcare, which focuses more on preventing problems rather than just treating them.

Of course, as more people use this kind of tech, it's important to handle their personal data responsibly. Protecting user privacy and being transparent about how data is used will be key to building trust and making sure these systems are used in a fair and ethical way.

7.5 Summary of Key Takeaways

To conclude, this thesis has demonstrated that:

- Wearable 9-axis IMU sensors can provide accurate, reliable, and practical measurements of running biomechanics.

- A minimal sensor setup, combined with effective signal processing and validated metrics, offers meaningful insights into athlete performance and fatigue.
- The system's portability and affordability position it as a valuable tool for diverse users from professional athletes to rehabilitation patients.
- Addressing practical challenges related to sensor placement, data interpretation, and user engagement is critical.
- Future developments in real-time feedback, multimodal sensing, and machine learning promise to transform biomechanical monitoring into a more accessible and powerful resource.
- The broader societal impact of such wearable technology spans health promotion, injury prevention, and cost reduction in healthcare.

These conclusions provide a strong foundation for continued innovation in wearable biomechanics, fostering improved athletic performance and injury prevention through accessible technology.

7.6 Limitations and critical reflections

While the developed wearable system demonstrated promising results in measuring and interpreting running biomechanics, several limitations must be known to highlight areas for future refinement.

Firstly, despite implementing calibration and filtering techniques, IMU-based systems are inherently prone to drift particularly during longer runs or high-intensity sessions. These factors can create noise for measurements if not carefully managed.

Secondly, while the system's performance was benchmarked against commercially available devices, it did not include lab equipment such as optical motion capture systems or force plates for all metrics. This restricts the level of validation and may leave some parameters subject to interpretation bias.

Finally, user experience aspects such as long-term comfort, battery performance, and real-world robustness (different enviroments) were not extensively tested. Addressing these practical concerns will be crucial for widespread adoption and daily use.

These limitations provide important context for interpreting the findings and serve as a guide for future system optimization and broader evaluation studies.

7.7 Final reflection and outlooks

This project is more than just a technical study it's a step toward making biomechanical feedback available to everyone. By proving that even a simple, lightweight IMU sensor setup can give useful and reliable information, it opens the door for athletes, therapists, and regular users to better understand and improve how they move.

As people become more focused on health and fitness, and technology becomes more a part of everyday life, wearable biomechanics could become an important tool for staying healthy, avoiding injuries, and learning how to move properly. The lines between sports science, healthcare, and consumer gadgets are starting to blur, and systems like this one could help connect them.

In the future, as sensor designs get better, apps become easier to use, and analytics get smarter, these tools will be even more powerful. We're heading toward a time when real-time movement tracking is just part of everyday life helping people stay safe, move more efficiently, and feel more confident in their bodies.

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