



Dynamic Motion Capturing

Anil Kumar S*ETE**B.I.T (V.T.U)**Bangalore India***Dev S Shah***ETE**B.I.T (V.T.U)**Bangalore India***Tarun Patel S***ETE**B.I.T (V.T.U)**Bangalore India***Vijay Kumar***ETE**B.I.T (V.T.U)**Bangalore India*

Abstract: This paper investigates dynamic motion capturing in fitness exercises, focusing on bicep curls and planks. Utilizing the MediaPipe framework and MPU6050 sensor, we analyse elbow angles, alignment, and errors such as loose upper arm and weak peak contraction. Results indicate the necessity of IoT devices for detailed bicep curl analysis, while plank exercises demonstrate alignment importance without IoT integration. Findings highlight the potential of motion-capturing technology in fitness assessment and training. The study contributes to understanding exercise biomechanics and underscores the significance of proper form. Future research should explore the further integration of IoT devices and refine analysis techniques for a comprehensive fitness assessment.

Index Terms: Dynamic Motion Capturing, IoT Sensors, exercise correction, Mediapipe, Framework

I.Introduction:

Dynamic motion-capturing technology has emerged as a pivotal tool in various domains, notably, fitness and healthcare. Precisely tracking and analyzing movements offers valuable insights into performance, form, and biomechanics. In fitness, where exercises like the bicep curl and plank are fundamental to training regimens, accurate motion analysis can optimize workouts, prevent injuries, and enhance overall results.

The bicep curl, a classic resistance exercise targeting the biceps brachii muscle, is frequently incorporated into strength training routines. Proper form is crucial for maximizing muscle engagement and minimizing strain. Similarly, the plank exercise, renowned for its efficacy in core strengthening, demands precise alignment to ensure optimal muscle activation and injury prevention.

This paper aims to analyze these exercises utilizing the MediaPipe framework and the MPU6050 sensor for dynamic motion capturing. MediaPipe, a versatile framework for building multimodal applied machine learning pipelines, offers robust capabilities for real-time motion analysis. Meanwhile, the MPU6050 sensor, known for its precise measurement of motion, acceleration, and orientation, provides invaluable data for understanding exercise kinetics.

By leveraging these technologies, we seek to examine various parameters during the execution of bicep curls and planks, including joint angles, alignment, and potential errors such as loose upper arm or weak peak contraction. Through detailed analysis, we aim to elucidate the effectiveness of these exercises and identify areas for improvement. Furthermore, we explore the role of IoT integration in enhancing the depth and accuracy of motion analysis, particularly in exercises like the bicep curl where detailed insights into muscle activation patterns and form discrepancies are critical.

In summary, this paper endeavours to harness the power of dynamic motion-capturing technology to enhance our understanding of key fitness exercises, ultimately contributing to improved training methodologies and better outcomes for individuals pursuing fitness goals.

II. Literature Review

Traditional methods for motion capture in fitness and healthcare have evolved, encompassing manual observation, video analysis, and marker-based motion capture systems. While these methods have been widely used, they often face challenges such as limited accuracy, subjectivity in analysis, lack of real-time feedback, and constraints in cost and portability.



Traditional Method	Description	Challenges
Manual Observation	Direct visual assessment of movement quality by trainers or healthcare professionals.	- Subjective interpretation - Lack of quantitative data
Video Analysis	Frame-by-frame analysis of recorded videos to examine movement patterns.	- Time-consuming and labour-intensive - Lack of real-time feedback
Marker-based Motion Capture	Tracking reflective markers placed on body parts using multiple cameras.	- Expensive and specialized equipment - Occlusion and marker dropout issues

Manual Observation: Historically, trainers and healthcare professionals have relied on manual observation to assess movement quality during exercises or physical activities. While this method allows for direct visual assessment of form and technique, it is inherently subjective and may be prone to bias.

Video Analysis: Recording videos of individuals performing exercises and subsequently analyzing the footage frame by frame is another common method for motion capture. Video analysis provides a detailed examination of movement patterns and allows for precise feedback on form and technique. However, it can be time-consuming and labour-intensive, particularly when analyzing large datasets or complex movements.

Marker-based Motion Capture Systems: Marker-based motion capture systems involve placing reflective markers on specific body parts and using multiple cameras to track the movement of these markers in 3D space. While marker-based systems offer high accuracy, they can be expensive, require specialized equipment, and may not provide real-time feedback. Additionally, occlusion and marker dropout issues can limit their effectiveness, especially in dynamic environments.

Challenges with Traditional Methods:

Traditional motion capture methods face several challenges that limit their applicability and effectiveness in fitness and healthcare settings:

Limited Accuracy: Manual observation and video analysis rely on subjective interpretation and may not provide precise quantitative data on movement parameters.

Subjectivity in Analysis: Manual observation and video analysis are susceptible to observer bias, leading to inconsistencies in movement assessment.

Lack of Real-time Feedback: Traditional methods often lack real-time feedback capabilities, making it difficult for individuals to adjust their movements or receive immediate guidance during exercises.

Cost and Portability Constraints: Marker-based motion capture systems can be expensive and require specialized equipment and infrastructure, limiting their accessibility and scalability for widespread use.

YOLOv7-Pose vs MediaPipe

YOLOv7	MediaPipe
Multiperson Pose Estimation Model	Single Person Pose Estimation Model
17 Keypoints	33 Keypoints
Default Input Size: 960P	Default Input Size: 256x256
Detection is done on Every Frame	Detection + Tracking

Integration of OpenCV and IMU Sensors:

To overcome the limitations of traditional methods, researchers have explored innovative approaches that leverage emerging technologies such as computer vision and inertial sensing. The integration of OpenCV with IMU sensors offers a promising solution for enhanced motion capture in fitness and healthcare applications.

OpenCV: OpenCV provides advanced computer vision algorithms for analyzing video footage and extracting relevant motion features. Its real-time processing capabilities enable instantaneous analysis of movement patterns, facilitating immediate feedback on form and technique.

Dynamic Motion Capturing

IMU Sensors: IMU sensors measure acceleration, angular velocity, and sometimes magnetic field data, offering additional motion parameters for comprehensive analysis. IMUs are compact, portable, and cost-effective, making them suitable for wearable applications in diverse settings.

The integration of OpenCV and IMU sensors represents a significant advancement in motion capture technology, addressing key challenges associated with traditional methods. By combining computer vision and inertial sensing capabilities, this approach enables accurate, real-time motion analysis with objective feedback, enhancing the effectiveness of fitness training, rehabilitation, and healthcare interventions.

III. Methodology

Setup for Capturing Motion Data:

The motion capture setup comprises hardware components and software frameworks to accurately capture and analyse movements during exercises. The hardware includes IMU sensors such as the MPU6050 sensor, which measures acceleration, angular velocity, and sometimes magnetic field data. These sensors are typically attached to key body locations using wearable devices or adhesive mounts. The MPU6050 sensor communicates with a microcontroller or a development board, such as Arduino or Raspberry Pi, to collect and process motion data.

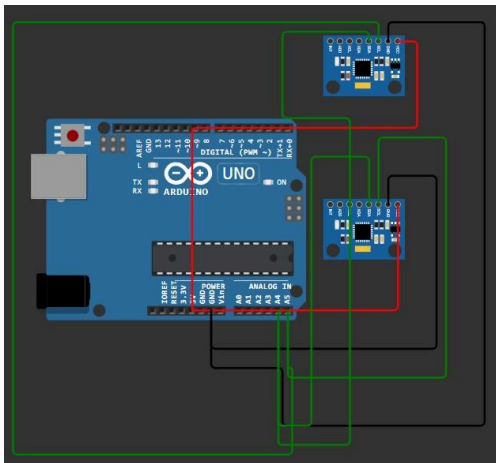


Fig: Schematic representation of the motion capture setup with MPU6050 sensors and microcontroller.

On the software side, the motion data is processed using frameworks like MediaPipe. MediaPipe provides a suite of machine-learning solutions for various tasks, including pose

Data Collection Process:

Analysis:

- Analytical techniques are applied to the motion data to extract relevant insights, such as peak contraction strength, stability, and symmetry.
- Statistical methods may be employed to quantify the extent of errors and deviations from optimal form.

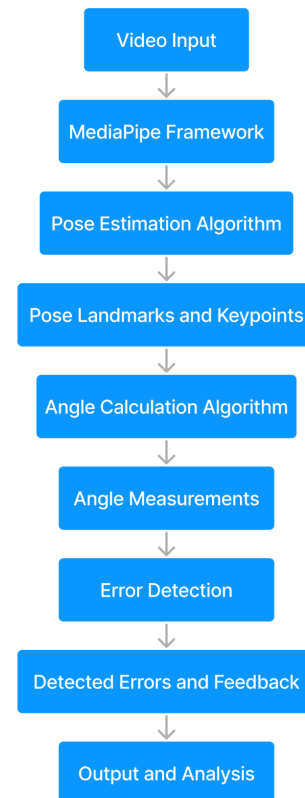


Fig: Data collection process during bicep curl and plank exercises with Images or Videos

Algorithms and Techniques:

Angle Calculation:

- For the bicep curl exercise, the angles of both elbows are calculated using trigonometric functions based on the orientation data from the IMU sensors attached to the upper arms.
- In the plank exercise, the angle between the elbows and the alignment of the hips with the shoulders are computed using similar principles.

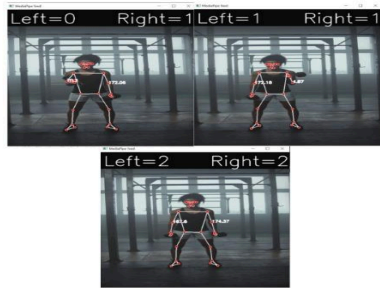
Dynamic Motion Capturing

Error Detection:

- Error detection algorithms analyze the calculated angles and compare them against predefined thresholds or reference values.
- Common errors such as loose upper arm or improper hip alignment are detected based on deviation from expected values.

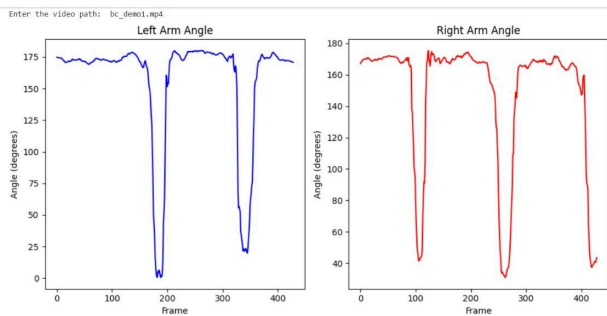
Bicep Curl Analysis:

Methodology: Motion Capture, MediaPipe, and IMU sensors were utilized to capture and analyze the bicep curl. Participants wore IMU sensors while performing the exercise. Data from Motion Capture and MediaPipe were synchronized for integrated analysis.



Data Analysis: Joint kinematics, muscle activation, and movement dynamics were examined. Integrated data revealed detailed patterns of motion and muscle recruitment during the bicep curl.

Error Detection:



Result: The combined approach provided insights into exercise biomechanics, highlighting variations in technique and muscle recruitment. Graphs illustrating results can be inserted here.

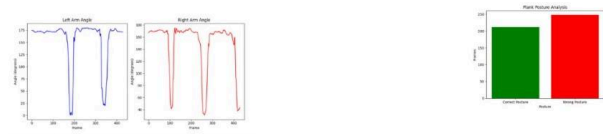
Plank Analysis:

Methodology: Motion Capture, MediaPipe, and IMU sensors were employed to capture and analyze plank exercises. Participants wore IMU sensors while performing the plank. Data from Motion Capture and MediaPipe were synchronized for comprehensive analysis.



Data Analysis: Joint kinematics, muscle activation, and movement dynamics were assessed. Integrated data unveiled detailed insights into motion and muscle engagement during the plank.

Error Detection:



Result: The integrated approach offered valuable insights into plank biomechanics, highlighting variations in technique and muscle activation. Graphs depicting results can be inserted here.



References

- [1] H. Yang et al., “Multi-Inertial Sensor-Based Arm 3D Motion Tracking Using Elman Neural Network,” *Journal of Sensors*, vol. 2022. Hindawi Limited, pp. 1–11, May 16, 2022. doi: 10.1155/2022/3926417.
- [2] E. Digo, S. Pastorelli, and L. Gastaldi, “A Narrative Review on Wearable Inertial Sensors for Human Motion Tracking in Industrial Scenarios,” *Robotics*, vol. 11, no. 6. MDPI AG, p. 138, Dec. 02, 2022. doi: 10.3390/robotics11060138.
- [3] L.-T. Duan, M. Lawo, Z.-G. Wang, and H.-Y. Wang, “Human Lower Limb Motion Capture and Recognition Based on Smartphones,” *Sensors*, vol. 22, no. 14. MDPI AG, p. 5273, Jul. 14, 2022. doi: 10.3390/s22145273.
- [4] R. Haratian, “Motion Capture Sensing Technologies and Techniques: A Sensor Agnostic Approach to Address Wearability Challenges,” *Sensing and Imaging*, vol. 23, no. 1. Springer Science and Business Media LLC, Jul. 20, 2022. doi: 10.1007/s11220-022-00394-2.
- [5] A. P. Singh and D. Agarwal, “Webcam Motion Detection in Real-Time Using Python,” 2022 International Mobile and Embedded Technology Conference (MECON). IEEE, Mar. 10, 2022. doi: 10.1109/mecon53876.2022.9752059.