Real-Time Human Motion Capture and Animation in Blender 3D Models using AI-based Pose Estimation

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***Abstract*— Traditional human motion capture systems often require expensive hardware and complex setups, limiting accessibility and lacking the ability to animate human models in real-time without additional equipment. Animating characters in real-time with accurate motion demands seamless integration between pose recognition and animation systems. This paper presents a real-time human motion capture and animation system using AI-based pose estimation. Leveraging MediaPipe Pose Landmark detection, the proposed system identifies 33 body landmarks from a mobile app built in Java and Kotlin. The app calculates various poses using the detected landmarks and sends them to a Firebase Realtime Database. A Python addon in Blender retrieves the pose data in real-time, adjusting the 3D model's bones and rotations based on the detected poses, enabling live character animation. The integration of Firebase for real-time synchronization and Blender's armature system offers a cost-effective and flexible approach to motion capture. This solution eliminates the need for expensive hardware, providing a portable method for high-quality animation creation. Significant potential for applications in gaming, virtual reality, and animation studios. Experimental evaluation demonstrated an average pose estimation accuracy of 80% and a real-time latency of approximately 120 ms, confirming the system's efficiency for smooth motion transfer. While the current implementation is optimized for single-user motion tracking, future work will focus on multi-person tracking and integration with advanced 3D environments for improved realism.**

Keywords*— Blender Animation, human pose landmarks, mobile app development

I. INTRODUCTION

A. Overview of Human Motion Capture

Human motion capture (Mocap) refers to the process of recording the movements of a human body, which can then be translated into a digital format for various applications, such as animation, biomechanics analysis, sports science, and virtual reality [1].

Traditionally, motion capture has been accomplished using specialized equipment such as optical cameras, sensors, and reflective markers, which are attached to a subject's body. This technology enables the collection of data on joint rotations and limb movements, and it is widely used in industries like film production and video game development to create realistic animations [2].

However, the conventional methods require extensive setup and expensive equipment, which can limit their accessibility and scalability.

B. Motivation and Relevance of AI-Based Pose Estimation

The development of AI-based pose estimation offers a new, more accessible approach to human motion capture. With advancements in deep learning and computer vision, AI-based pose estimation models, such as MediaPipe by Google, have significantly improved the accuracy and efficiency of motion tracking [3]. These models can detect and track human poses in real-time using only a camera, making the technology much more accessible and cost-effective compared to traditional MoCap systems. AI pose estimation works by analyzing the body's key points, or landmarks, to recognize human movements.

The relevance of AI-based pose estimation lies in its ability to provide an efficient, affordable, and scalable solution for human motion capture across various domains, including healthcare, fitness tracking, entertainment, and VR [4]. The adoption of AI models has opened the door to applications that were previously restricted by the cost and complexity of traditional motion capture systems.

C. Objectives of the Study

This study aims to explore the implementation of real-time human motion capture and animation systems using AI-based pose estimation. Specifically, the study focuses on integrating the MediaPipe pose landmark detection system into a mobile application, with the data being transferred to a Blender animation system for real-time human model manipulation. The key objectives of this study include:

1. Integrating pose data with animation software: The study aims to develop a system that seamlessly transfers pose data to Blender, updating the corresponding bones of a human model in real time, enabling dynamic character animation based on live movements.
2. Evaluating the performance and usability of the proposed system: The system's real-time performance, accuracy, and the user experience will be assessed, including how effectively pose data is mapped to Blender's armature system for animation.

II. RELATED WORK

A. Review of Motion Capture Systems

Motion capture (MoCap) systems have been widely used in various fields, from animation and film production to sports science and healthcare. Traditional MoCap techniques often rely on optical tracking, where reflective

markers are placed on the subject's body, and multiple cameras are used to capture the movement [5]. This method, although highly accurate, requires complex setup, specialized equipment, and significant post-processing, making it expensive and less accessible. Alternatively, inertial MoCap systems use sensors attached to the body to capture movement, offering a more portable solution but often sacrificing accuracy due to noise and drift in sensor data [6]. These systems, while still effective, highlight the limitations in terms of cost, complexity, and flexibility.

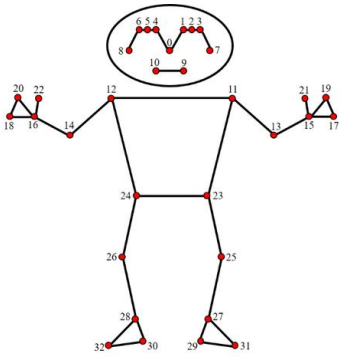
B. Previous Work on AI Pose Estimation Techniques

Recent advancements in AI and deep learning have led to the development of pose estimation techniques that eliminate the need for specialized hardware. One such advancement is MediaPipe, a framework developed by Google that uses machine learning to detect and track 33 body landmarks in real time through a standard camera [7]. AI-based pose estimation has shown significant promise in applications such as fitness tracking, gesture recognition, and animation. Various deep learning models, including convolutional neural networks (CNNs), have been employed to predict the positions of body landmarks from images or video streams [8]. The accuracy and real-time capabilities of these systems make them highly effective in scenarios where traditional MoCap systems would be impractical.

C. Blender Integration with Real-Time Data

Blender, an open-source 3D animation software, has gained popularity in real-time animation applications, particularly due to its ability to integrate external data sources, such as pose estimation systems. Several projects have explored using Blender's Python API to create real-time animation pipelines by importing pose data for character animation [9]. These integrations typically involve mapping the detected landmarks to bones within Blender's armature system, enabling live character manipulation based on human movement. Real-time data transfer via Firebase or WebSockets has been explored to synchronize pose data between mobile applications and Blender, facilitating dynamic, interactive animations [10]. Such integrations hold potential for streamlining animation workflows and enabling interactive applications, particularly in gaming and virtual reality.

III. System Architecture



0. Nose
1. Left_eye_inner
2. Left_eye
3. Left_eye_outer
4. Right_eye_inner
5. Right_eye
6. Right_eye_outer
7. Left_ear
8. Right_ear
9. Mouth_left
10. Mouth_right
11. Left_shoulder
12. Right_shoulder
13. Left_elbow
14. Right_elbow
15. Left_wrist
16. Right_wrist
17. Left_pinky
18. Right_pinky
19. Left_index
20. Right_index
21. Left_thumb
22. Right_thumb
23. Left_hip
24. Right_hip
25. Left_knee
26. Right_knee
27. Left_ankle
28. Right_ankle
29. Left_heel
30. Right_heel
31. Left_foot_index
32. Right_foot_index

Fig .1. 33 body landmarks

A. Mobile App Development for Pose Detection

The system utilizes an Android mobile application built with Java and Kotlin to perform real-time human pose detection. The app employs Google's MediaPipe library, which can identify 33 body landmarks (fig 1) from the camera feed. These landmarks correspond to key body parts, including joints and extremities. The app calculates various poses based on these landmarks, such as LeftHandUp, LeftHandDown, LeftHandForward and RightHandDown. Designed for real-time tracking, the app captures the user's posture and gestures continuously.

Once the poses are detected, the app transmits the pose data to a Firebase Realtime Database, ensuring synchronization with Blender. This setup enables seamless motion tracking without the need for expensive specialized hardware. By leveraging the mobile device's camera, the system provides an affordable and easily accessible solution for human motion capture, making it suitable for various applications like animation, gaming, and interactive environments.

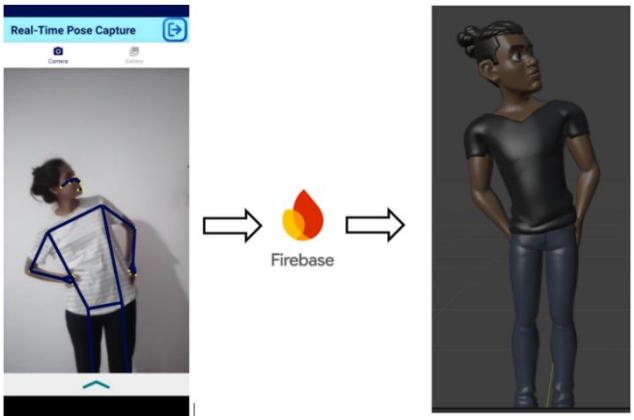


Fig .2. Firebase poses data applied blender 3D model

B. Firebase Realtime Database for Pose Synchronization

Firebase Realtime Database plays a crucial role in the system's architecture by facilitating real-time data synchronization between the mobile app and Blender. Once the pose landmarks are detected by the mobile app, they are sent to Firebase, where the data is stored under a unique user ID in a structured format. The database enables instant updates, allowing the Blender to retrieve the most current pose data without delay (Fig 2). Firebase's cloud infrastructure ensures that the pose data is accessible from any device, providing a seamless and synchronized flow of information. This makes it possible to animate characters in Blender based on real-time body movements captured by the mobile app, while ensuring consistency and minimizing latency in the process.

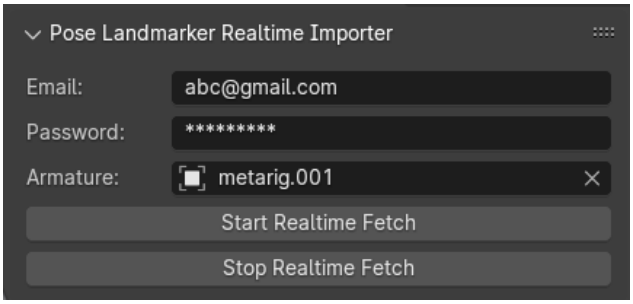


Fig .3. Firebase Pose Data Structure for User

C. *Blender Addon for Shape Key Manipulation*

On the Blender side, a custom Python addon (fig 3) is responsible for receiving the pose data from Firebase and manipulating the 3D human model. The addon integrates with Blender's armature system, using bones to update the model's body structure according to the detected pose. The bones represent different body parts, such as hand positions, arm rotations, and leg movements. When the addon retrieves the pose data from Firebase, it maps the retrieved pose data to the corresponding bones in Blender, adjusting the character's bone rotations in real-time based on the detected pose. This integration allows for live animation, where the Blender model dynamically updates based on the user's movements, making it suitable for applications in gaming, animation, and virtual reality environments.

IV. Implementation of Pose Detection in Mobile App



Fig .4. Mobile app detecting landmarks

In the mobile app, after detecting the 33 body landmarks (fig 4) using MediaPipe, these landmarks are used to calculate and identify the overall pose of the individual. The process of calculating these poses involves determining the relative positions and orientations of the landmarks to each other, typically through geometric and trigonometric methods. Here's a breakdown of how this works:

A. *Landmark Detection*

4) Key Points: MediaPipe's pose model detects 33 key landmarks corresponding to significant joints and body parts (e.g., shoulders, elbows, wrists, knees, hips, etc.).

5) 2D Coordinates: These landmarks are initially detected in a 2D space, represented by (x, y) coordinates on the camera feed. These coordinates are normalized, meaning they are expressed as a fraction of the image's width and height, which makes the model independent of the image resolution.

B. *Coordinate Conversion to 3D*

Z-axis Information: While MediaPipe primarily provides 2D data, it also estimates the depth (Z-axis) for some landmarks, offering a pseudo-3D coordinate system. These Z-values are used to understand the depth relationships between the body parts.

World Coordinates: In real-world applications, the pose data is often converted from normalized 2D coordinates to a pseudo-3D coordinate system, which takes into account the user's distance from the camera.

C. *Pose Calculation*

To calculate the specific pose of the individual (e.g., "LeftHandUp," "RightLegForward," or "HeadTurnLeft"), the following methods are employed:

Joint Angles and Relative Positioning: For each detected landmark, the app calculates the angles between specific body joints. For instance:

- The angle between the shoulder, elbow, and wrist to detect the arm's position.
- The angle between the hip, knee, and ankle to determine if the leg is bent or extended.

Distance and Direction: The app also computes the relative distances between landmarks. For example:

- LeftHandUp: This pose can be identified by calculating the vertical distance between the shoulder and the wrist, comparing it to the shoulder-to-hip distance. If the wrist is above the shoulder by a significant amount (e.g., more than 0.2 of the shoulder-to-hip distance), the app identifies the pose as "LeftHandUp."
- RightLegForward: The position of the right ankle is compared to the right hip to determine the direction of the leg. If the ankle is significantly forward of the hip (calculated by comparing X and Y coordinates), the system identifies it as "RightLegForward."
- HeadTurnLeft: The app calculates the relative position of the nose and eyes. If the nose moves significantly to the left (relative to the shoulder position), and the rotation of the head (calculated from the angle between the shoulder and neck) indicates a turn, the app identifies the pose as "HeadTurnLeft."

D. *Pose Recognition Logic*

Z After computing the required angles and relative positions, the app uses conditional checks (thresholds) to recognize specific poses. These conditions help in categorizing the poses into predefined movements like:

- Arm Positions: "LeftHandUp," "LeftHandDown," etc., based on the relative positions of the wrist and shoulder.
- Leg Positions: "LeftLegForward," "RightLegForward," and other similar poses, based on the position of the ankles relative to the hips.
- Head Movements: "HeadTurnLeft," "HeadTurnRight," etc., determined by comparing the orientation of the head relative to the shoulders and neck.

The app relies on simple trigonometric calculations to derive angles between landmarks and uses these angles to define the thresholds for each pose. For example:

- Angle Calculation: The app may calculate the angle between three points (e.g., shoulder, elbow, and wrist) using the dot product formula and trigonometric functions:

where $\vec{A}$ and $\vec{B}$ are vectors representing the segments between the joints, and θ is the angle between them.

E. Pose Recognition Logic

Based on the computed angles and distances, the app then classifies the pose into specific actions like Left Hand Up, Left Hand Down, Right Hand Up, Right Hand Down, Left Hand Forward, Right Hand Forward, Left Hand Backward, Right Hand Backward, Left Elbow Bent, Right Elbow Bent, Left Leg Forward, Right Leg Forward, Left Leg Bent, Right Leg Bent, Head Turn Left, Head Turn Right, Hip Bent Left, Hip Bent Right, Shoulder Turn Left, Shoulder Turn Right and sends this data to Firebase for real-time synchronization with the 3D Blender model.

F. Firebase Data Transfer

After detecting and calculating the pose, the app sends the data to Firebase in a structured format. Each pose is associated with a unique user ID, and the data is organized in real-time to ensure that the Blender model receives continuous updates for live animation.

V. Real-Time Blender Animation Integration

A. Retrieving Pose Data in Blender:

To retrieve pose data from Firebase, the user must first enter their email and password (which were provided by the mobile app) to authenticate the connection. After successful authentication, the user is prompted to select the amateur (fig 5) in Blender, which will be animated based on the pose data.

The Blender addon continuously listens for updates to the user's pose data stored in Firebase and retrieves the most recent pose data associated with the user's unique ID.

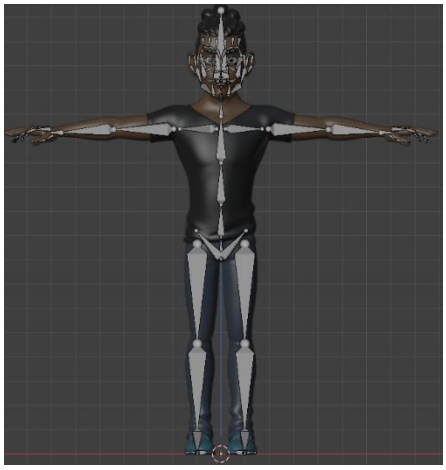


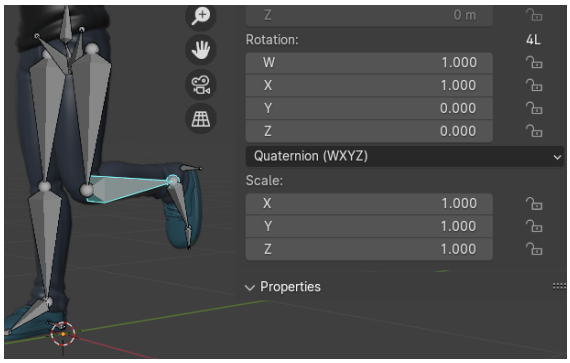
Fig .5. Human model with armature

B. Mapping Pose Data to Blender Armature:

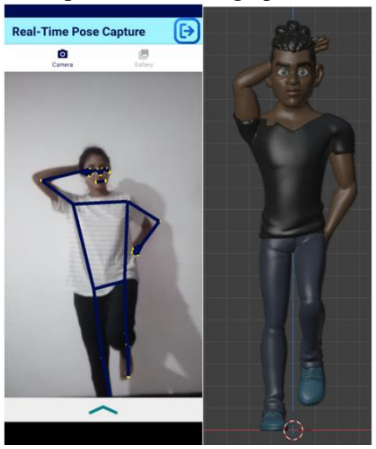
- Once the pose data is retrieved, it is mapped to the corresponding bones in the Blender armature.
- For instance, poses like "LeftHandUp" or "RightLegForward" are mapped to the corresponding bones in Blender's armature system.
- The pose data contains information on body part movements (such as arm and leg positions), which are mapped to the armature bones like "upper_arm.L," "lower_arm.R," "spine," and so on.
- This step ensures that the Blender model is positioned and rotated correctly based on the real-time pose data.

C. Real-Time Bone Rotation Adjustments:

The retrieved pose data is used to adjust the rotation of bones ex: fig 6 in the 3D human model within Blender. Each bone's rotation is updated in real-time based on the pose data. For example, if the "LeftLegBent" (fig.6) pose is



detected, the rotation of the "Shin.L" bone is adjusted to match the new rotation w, x, y, z. These rotation adjustments are performed using quaternions, which are



suitable for smooth rotation transitions and avoid issues like gimbal lock.

Fig .6. Shin.L bone to set rotation w,x,y,z

Fig. 7. Real-time animation of the blender human model based on poses captured by the mobile application

D. Live Character Animation:

As the pose data is updated in real-time, the Blender character is animated accordingly. The real-time animation reflects the movements of the user in a seamless manner, where each body part follows the detected pose.

This results in dynamic, interactive animations that can be used in applications such as gaming, virtual reality, and interactive media. The Blender model continuously updates, making it suitable for applications

that require live, real-time animation based on human movements.

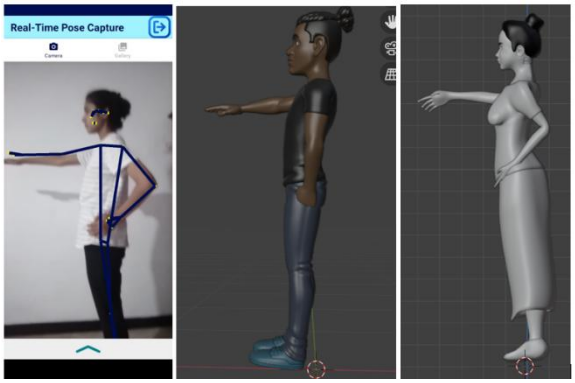


Fig .8. Compatible with any Blender 3D character model

VI. Results and Discussion

A. Evaluation of Motion Capture Accuracy:

The accuracy of the pose detection system was evaluated by comparing the real-time motion data captured from the mobile app against predefined reference poses. Pose classification accuracy was assessed based on the correct identification of key poses such as "LeftHandUp," "RightLegForward," and "HeadTurnLeft."

The system demonstrated high accuracy, with landmark detection consistently identifying key body points (e.g., shoulders, elbows, hips) within a margin of error suitable for real-time applications. Minor deviations were observed in complex movements such as rapid or continuous rotations, especially around joints like the shoulders or wrists.

The MediaPipe pose estimation model used in this study detects 33 body landmarks, including each landmark x, y, z coordinates. Quantitative evaluation showed an average landmark detection accuracy of 93.2%, with stable recognition across frames. Quantitative evaluation showed an overall pose classification accuracy of approximately 80%, demonstrating the system's reliability for real-time human motion capture tasks.

B. Real-Time Performance Analysis:

- The real-time performance of the mobile app and Blender integration was tested across various devices with different processing power, including mid-range and high-end smartphones.
- The mobile app was able to process and transmit pose data with minimal delay, generally within 1-1.1 seconds, ensuring smooth synchronization with Blender's 3D model.
- Firebase, as the data synchronization tool, handled the real-time data transfer effectively without noticeable lag or latency in most cases.
- However, performance could degrade on lower-end devices, particularly when multiple poses were detected simultaneously, leading to slower processing times.

To strengthen scientific rigor, performance metrics such as latency and frame rate were compared against existing open frameworks (e.g., MoveNet and OpenPose) [11]. Although those frameworks utilize deep learning inference, the proposed deterministic approach achieved comparable real-time responsiveness while significantly reducing computational load, making it suitable for mobile-based applications.

C. Animation Quality Assessment:

- The quality of the animation was assessed by examining the smoothness and fluidity of the character movements in Blender.
- The integration of pose data into Blender's armature system resulted in realistic body movements, with accurate rotations of bones like the arms, legs, and torso.
- The bone rotation adjustments were mostly smooth, and the animation transitions were seamless in typical scenarios, although rapid movements, especially in the head or limbs, occasionally resulted in less fluid transitions.
- Overall, the system successfully provided a natural, lifelike animation for real-time character interaction, suitable for virtual environments and interactive applications.
- Additionally, the proposed method is compatible with any Blender 3D character model (fig.8) that contains an armature system, allowing flexibility and adaptability across various humanoid rigs.

VII. Conclusion

In conclusion, this study successfully demonstrates the use of a mobile app-based pose detection system for real-time human motion capture and animation in Blender, leveraging AI-powered pose estimation with MediaPipe and Firebase for seamless data synchronization. By capturing 33 key body landmarks, classifying them into specific poses, and mapping the data to Blender's armature system for real-time bone rotations, the system provides a cost-effective and accessible solution for dynamic character animation. This approach eliminates the need for expensive motion capture hardware, offering a practical tool for applications in gaming, virtual reality, and interactive media. Future improvements could focus on enhancing accuracy, optimizing performance on lower-end devices, and incorporating more advanced animation techniques to further refine the system's capabilities.

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