

***APPLIED MATHEMATICAL MODELING FOR 3D KINEMATIC SPATIAL
RECONSTRUCTION IN A LOW-COST MONOCULAR WEBCAM-BASED
SQUAT ANALYSIS SYSTEM***

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ABSTRACT

*Squat is a fundamental exercise for improving lower body strength; however, improper execution may increase the risk of musculoskeletal injury. Conventional motion analysis systems, such as marker-based technologies, provide high accuracy but require expensive equipment and controlled environments, while monocular camera-based approaches often suffer from limited three-dimensional representation. Therefore, this study proposes a low-cost squat analysis system, *gui_mocap*, which integrates monocular computer vision with vector-based mathematical modeling for real-time motion analysis. The system employs pose estimation to detect body landmarks and reconstructs joint kinematics in three-dimensional space using geometric vector operations. Knee joint angles are computed using the dot product formulation, and an Exponential Moving Average (EMA) filter is applied to improve measurement stability. Experimental evaluation was conducted using multiple squat repetitions to analyze motion patterns and consistency. The results demonstrate that the system can accurately identify key movement phases, including standing, deep flexion, and return to standing, while producing smooth and stable joint angle trajectories. Furthermore, the system is capable of analyzing repeated movements and generating descriptive statistics, such as average joint angles and range of motion, indicating consistent performance across repetitions. This study contributes a practical and affordable solution for real-time motion analysis using a monocular webcam, with potential applications in home-based exercise monitoring and basic rehabilitation.*

Keywords: *Squat Analysis, Pose Estimation, Joint Angle Measurement, Monocular Vision, Motion Tracking, Repetition Analysis, Applied Mathematical Modeling.*

1. Introduction

The increasing interest in home-based exercise has created a growing demand for accessible and affordable tools to monitor human movement. Among various exercises, the squat is widely recognized as a fundamental movement for improving lower body strength and overall physical performance. However, improper squat execution may lead to excessive joint loading and increase the risk of musculoskeletal injuries, particularly in the knee and lower back regions (Escamilla, 2001; Fry et al., 2003; Schoenfeld, 2010). Therefore, accurate motion analysis is essential to ensure safe and effective exercise performance.

Conventional motion analysis systems, such as marker-based technologies, provide highly accurate three-dimensional (3D) kinematic measurements and are widely used in biomechanics research (Baker, 2006; Richards, 1999; Windolf et al., 2008). Nevertheless, these systems require expensive equipment, controlled laboratory environments, and complex calibration procedures, which limit their applicability for everyday use. To address these limitations, low-cost markerless approaches based on monocular cameras and computer vision have been increasingly explored.

Recent advances in pose estimation, including OpenPose and MediaPipe, have enabled real-time detection of human body landmarks using standard cameras (Cao et al., 2021; Kammoun et al., 2022; Lugaresi et al., 2019; Newell et al., 2016; Toshev & Szegedy, 2014). These

approaches offer a practical alternative for motion analysis and have been applied in fitness monitoring and rehabilitation contexts (Dibenedetto et al., 2025; Moeslund et al., 2006; Pfister et al., 2014).

In addition, recent studies have explored high-resolution and video-based pose estimation models that further improve accuracy and temporal consistency (Desmarais et al., 2021; Kocabas et al., 2019; Sun et al., 2019). Comprehensive surveys also highlight the rapid development of pose estimation techniques and their applications in motion analysis (Poppe, 2010). However, existing low-cost squat monitoring systems still face several important limitations. First, joint angle estimation from monocular images often suffers from reduced accuracy due to the lack of true depth information (Martinez et al., 2017; Shotton et al., 2013). Second, real-time robustness is affected by environmental factors such as lighting conditions, camera positioning, and occlusion. Third, many approaches rely on complex deep learning models that reduce interpretability and limit usability for non-expert users in home environments.

Several studies have attempted to address these challenges by incorporating three-dimensional reconstruction techniques or advanced learning-based models. While these approaches improve accuracy, they typically require large datasets, high computational resources, or multi-camera setups, which reduce their practicality for real-time and low-cost applications. In addition, most existing systems focus primarily on pose detection rather than providing interpretable kinematic analysis for evaluating movement quality and repetition consistency.

In addition to accuracy challenges, practical deployment of motion analysis systems is affected by several factors, including variability in user posture, camera positioning, lighting conditions, and partial occlusion of body parts (Richards, 1999; Scataglini et al., 2024; Schoenfeld, 2010). These factors can significantly influence the robustness and reliability of pose estimation results (Toshev & Szegedy, 2014; Windolf et al., 2008; Xue, 2025). Moreover, recent developments in artificial intelligence emphasize the importance of interpretability and transparency, particularly in human-centered applications where understanding system behavior is essential (Nagymáté & Kiss, 2018; Needham et al., 2021; Newell et al., 2016; Vishwakarma et al., 2015).

To address these challenges, mathematical modeling can be employed to reconstruct spatial relationships between body segments. By representing joints as vectors in a three-dimensional Euclidean space, joint angles can be computed using geometric operations such as the dot product, providing a consistent and interpretable representation of motion (Anton, H & Rorres, C, 2013; Fazrol & A. S. R., 2009; Rambely & Fazrolrozi, 2012; Strang, G, 2006). Despite this potential, the integration of monocular vision with vector-based geometric modeling for real-time squat analysis remains insufficiently addressed in existing low-cost motion analysis systems.

This study aims to develop a low-cost squat motion analysis system capable of accurately computing joint angles and analyzing movement consistency in real time using a monocular camera. The proposed system integrates real-time pose estimation with vector-based mathematical modeling to reconstruct joint kinematics in three-dimensional space. Unlike purely data-driven approaches, the method emphasizes computational simplicity and interpretability through explicit geometric formulation. The proposed *gui_mocap* system provides an affordable and user-friendly solution for squat monitoring in home-based environments. The system enables real-time joint angle tracking, repetition analysis, and motion consistency evaluation, making it suitable for applications in fitness training and basic rehabilitation.

2. Literature Review

Human motion analysis has been widely studied in biomechanics and computer vision, particularly for applications in sports performance, rehabilitation, and human-computer interaction (Moeslund et al., 2006; Pfister et al., 2014; Scataglini et al., 2024). Existing approaches can generally be categorized into marker-based systems and markerless vision-based methods, each offering distinct advantages and limitations.

Marker-based systems, such as Vicon, are considered the gold standard due to their high accuracy in capturing three-dimensional (3D) motion (Antognini et al., 2025; Baker, 2006; Richards, 1999; Windolf et al., 2008). These systems provide reliable kinematic measurements and have been extensively used in biomechanical studies of squat movements (Escamilla, 2001; Fry et al., 2003; McKean et al., 2010; Schoenfeld, 2010). However, their reliance on specialized hardware, controlled environments, and complex calibration procedures makes them impractical for real-time and home-based applications (Heitzmann et al., 2022; Nagymáté & Kiss, 2018).

To overcome these limitations, markerless approaches based on computer vision have gained significant attention. Recent developments in pose estimation models, such as OpenPose and MediaPipe, enable real-time detection of human body landmarks from monocular images (Cao et al., 2017, 2021; Lugaresi et al., 2019; Newell et al., 2016; Toshev & Szegedy, 2014). These methods offer a low-cost and flexible alternative and have been applied in exercise monitoring and rehabilitation (Moeslund et al., 2006; Needham et al., 2021; Pfister et al., 2014; Torrejón et al., 2019; Xue, 2025). Nevertheless, monocular pose estimation methods exhibit limitations in accurately capturing three-dimensional joint relationships due to the absence of explicit depth information (Martinez et al., 2017; Shotton et al., 2013; Zhou et al., 2017).

Several studies have attempted to improve pose estimation accuracy by incorporating deep learning-based 3D reconstruction or multi-view camera systems. While these approaches can enhance spatial accuracy, they often require large training datasets, high computational resources, and complex system configurations (Dibenedetto et al., 2025; Dill et al., 2024). As a result, there exists a trade-off between accuracy and practicality, particularly in real-time and low-cost applications.

In the context of squat motion analysis, previous studies primarily focus on detecting joint positions or estimating kinematic parameters without providing interpretable representations of movement quality. Most existing systems emphasize pose detection performance rather than analyzing repetition consistency or biomechanical patterns, which are critical for evaluating exercise execution (Escamilla, 2001; McKean et al., 2010; Schoenfeld, 2010). This limitation reduces their usefulness in practical applications such as home-based training and rehabilitation.

To address interpretability and structural consistency, mathematical modeling approaches have been introduced. Vector-based kinematic modeling represents body segments as vectors in a three-dimensional Euclidean space, allowing joint angles to be computed using geometric operations such as the dot product (Anton, H & Rorres, C, 2013; Rambely & Fazrolrozi, 2012; Strang, G, 2006). Compared to purely data-driven methods, this approach provides a more transparent and physically interpretable representation of motion.

In addition, signal processing techniques are commonly used to improve the stability of motion data. Filtering methods such as the Exponential Moving Average (EMA) and Kalman filtering help reduce noise in joint angle measurements (Hunter, 1986; Welch & Bishop, 2006). However, these techniques introduce trade-offs between noise reduction and responsiveness, which must be carefully balanced in real-time systems.

Furthermore, recent developments in artificial intelligence emphasize the importance of interpretability and transparency in human-centered systems. Explainable Artificial Intelligence (XAI) has become an important research direction to improve trust and usability in AI-based systems (Arrieta et al., 2019; Barredo Arrieta et al., 2020; Haque et al., 2023). In the context of motion analysis, interpretability is particularly important for understanding movement patterns and providing actionable feedback to users.

Despite these advances, existing studies often treat pose estimation, kinematic modeling, and signal filtering as separate components, without integrating them into a unified framework for real-time motion analysis. Furthermore, there remains a lack of approaches that combine low-cost monocular vision with interpretable mathematical modeling to analyze both joint kinematics and movement consistency in repetitive exercises such as squats.

Therefore, this study proposes an integrated approach that combines monocular pose estimation, vector-based kinematic modeling, and signal filtering within a unified real-time system. By bridging these components, the proposed *gui_mocap* system aims to provide an efficient, interpretable, and practical solution for squat motion analysis in home-based environments.

Existing studies have demonstrated the feasibility of pose estimation and motion tracking; however, they often address these components in isolation rather than as an integrated system. As a result, current approaches are limited in providing a balance between accuracy, interpretability, and real-time performance in low-cost environments. This gap highlights the need for a unified framework that combines pose estimation, mathematical modeling, and signal processing into a single coherent system.

3. Research Methodology

This study follows an experimental system development approach, rather than a literature review methodology. The objective is to design, implement, and evaluate a low-cost squat motion analysis system using monocular computer vision and mathematical modeling.

The proposed system consists of four main stages: data acquisition, pose estimation, kinematic modeling, and result visualization. The overall workflow of the system, including data flow from video input to real-time joint angle visualization, is illustrated in Figure 1.

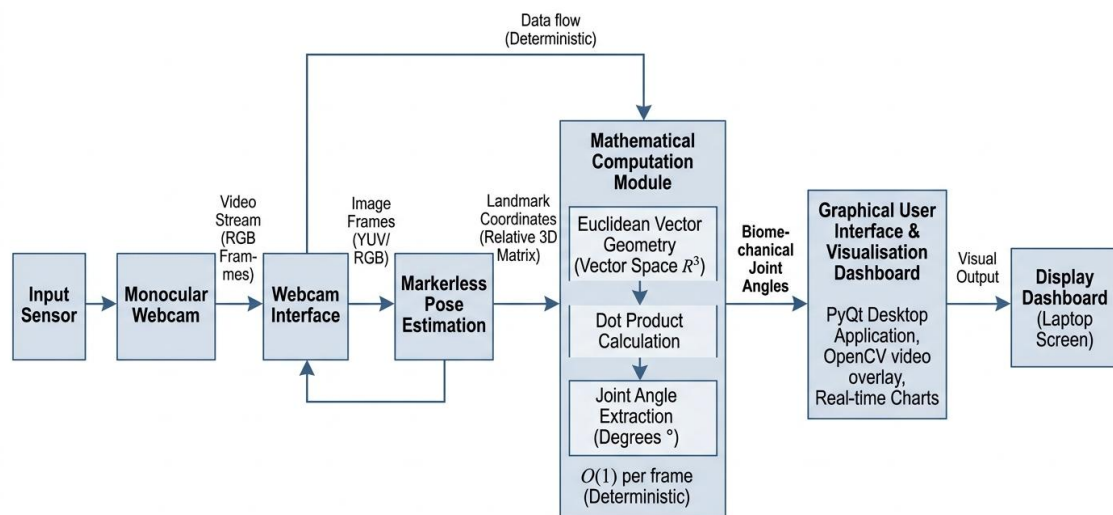


Figure 1. Workflow of the proposed system, including data acquisition, pose estimation, vector-based computation, and real-time visualization

Figure 1 illustrates the overall architecture of the proposed *gui_mocap* system and the data flow between its main components. The process begins with data acquisition using a monocular webcam, which captures real-time video of the subject performing squat movements. The captured frames are then processed by a pose estimation module to detect key body landmarks, including the hip, knee, and ankle joints. These landmarks are subsequently used in the kinematic modeling stage, where joint angles are computed using vector-based mathematical formulations. To improve the stability of the computed angles, a filtering module is applied before the results are visualized through a graphical user interface. This pipeline enables continuous real-time analysis of movement and joint kinematics.

3.1 Data Acquisition

Motion data are acquired using a monocular webcam with a resolution of 1080p at 30 frames per second. The camera is positioned in front of the subject to capture the full-body movement during squat exercises.

The experimental setup involves a subject performing multiple squat repetitions under normal indoor conditions. The recorded video frames serve as the input for further processing.

This setup is designed to simulate real-world usage scenarios, particularly for home-based exercise monitoring.

3.2. Pose Estimation and Landmark Detection

Each video frame is processed using a pose estimation model to detect human body landmarks. The model extracts key joint coordinates, particularly the hip, knee, and ankle, which are essential for squat motion analysis.

Each joint is represented as a point in a three-dimensional coordinate system:

$$P_i = (x_i, y_i, z_i)$$

where x_i and y_i represent image plane coordinates, and z_i represents relative depth estimation provided by the pose model.

3.3. Vector-Based Kinematic Modeling

To compute joint angles, the detected landmarks are modeled in a three-dimensional Euclidean space. The computation process is illustrated in Figure 2 and Figure 3.

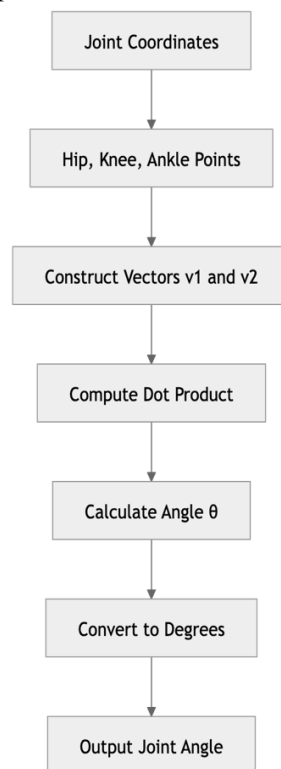


Figure 2. Flowchart of joint angle computation from detected body landmarks, including vector construction, dot product calculation, and angle extraction in degrees.

Figure 2 presents the vector-based kinematic modeling used to compute joint angles. In this representation, three key joints—hip, knee, and ankle—are modeled as points in a three-dimensional coordinate system. Two vectors are constructed from these points, representing adjacent body segments. The angle at the knee joint is then calculated using the dot product between the vectors. This geometric formulation allows for a consistent and interpretable computation of joint angles based on spatial relationships between body segments, providing a mathematically grounded approach to motion analysis.

Three points are defined:

- P_A (hip)
- P_B (knee)
- P_C (ankle)

Two vectors are constructed:

$$v_1 = P_A - P_B = \begin{bmatrix} x_A - x_B \\ y_A - y_B \\ z_A - z_B \end{bmatrix}$$

$$\vec{v}_2 = P_C - P_B = \begin{bmatrix} x_{CC} - x_B \\ y_C - y_B \\ z_C - z_B \end{bmatrix}$$

The joint angle is calculated using the dot product:

$$v_1 \cdot v_2 = |\vec{v}_1| |\vec{v}_2| \cos \theta$$

$$\theta = \arccos \left(\frac{v_1 \cdot v_2}{|\vec{v}_1| |\vec{v}_2|} \right)$$

The result is then converted into degrees for interpretation.

The geometric and mathematical representation of the proposed joint angle computation is illustrated in Figure 3, which describes the squat motion cycle, vector definitions, and the dot product formulation used to calculate the knee joint angle.

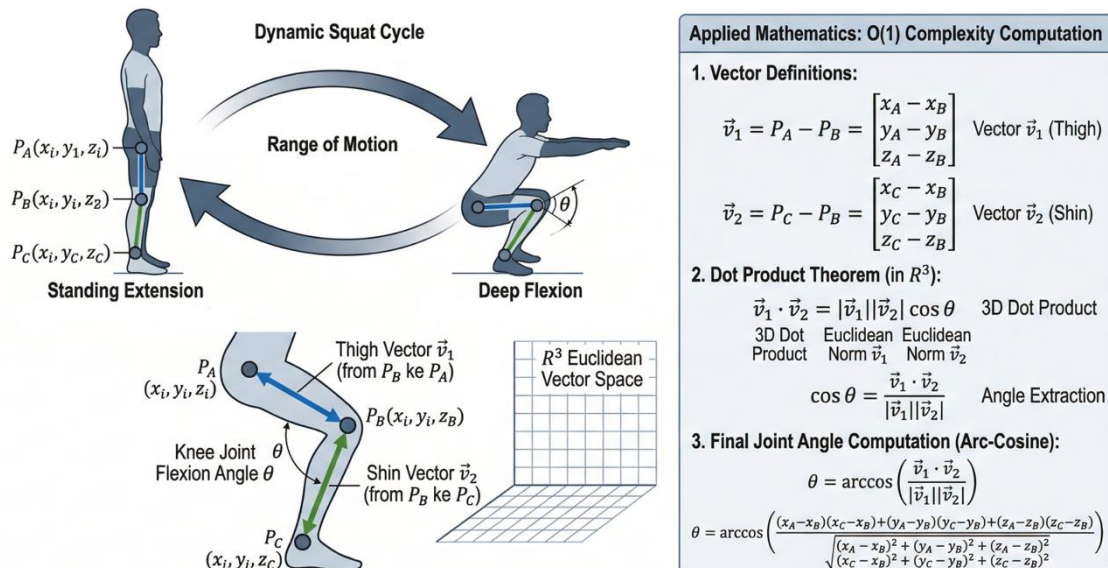


Figure 3. Geometric representation of squat motion and vector-based joint angle computation

The figure illustrates the dynamic squat cycle, definition of thigh and shank vectors, and the calculation of the knee joint angle using the dot product in three-dimensional Euclidean space.

3.4. Noise Reduction

To improve the stability of joint angle measurements, an Exponential Moving Average (EMA) filter is applied:

$$\theta_t = \alpha \theta_{\text{current}} + (1 - \alpha) \theta_{\text{previous}}$$

where α is the smoothing factor. In this study, $\alpha=0.2$ is used to balance responsiveness and stability.

3.5 Experimental Procedure and Evaluation

The system is evaluated through repeated squat movements performed by the subject. A total of multiple squat cycles are recorded and analyzed to assess system performance.

The evaluation focuses on:

- Joint angle accuracy (relative consistency)
- Motion pattern representation

- Repetition detection capability
- Statistical consistency across repetitions

Descriptive statistics, including average joint angles and range of motion, are computed to evaluate movement consistency.

3.6 Implementation Details

The system is implemented in Python and operates in real time on a standard computer without requiring specialized hardware. The output includes skeletal visualization and continuous joint angle tracking.

4. Results and Discussion

The performance of the proposed *gui_mocap* system was evaluated to assess its capability in capturing, processing, and interpreting squat movements using a monocular webcam. The evaluation focuses on joint angle computation, motion pattern representation, and repetition consistency under real-time conditions.

4.1 Single Squat Motion Analysis

The system was first tested on a single squat movement. The results are presented in Figure 4, which shows three key phases of the squat cycle: the initial standing position, the deep flexion position, and the final standing position.

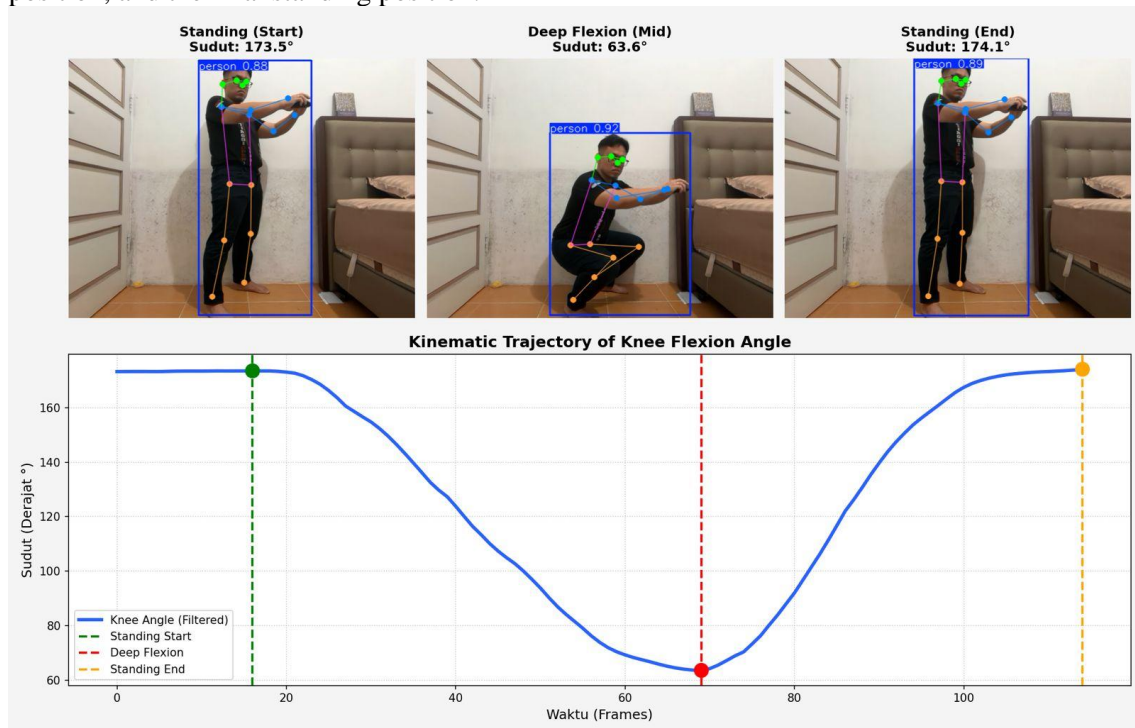


Figure 4. Squat motion analysis showing key phases (standing start, deep flexion, and standing end) along with the corresponding knee joint angle trajectory over time.

The performance of the proposed *gui_mocap* system was first evaluated using a single squat cycle. As illustrated in Figure 4, the system successfully detects key movement phases, including the standing (start), deep flexion (mid), and standing (end) positions. The corresponding knee joint angles are approximately 173.5°, 63.6°, and 174.1°, respectively.

These results demonstrate that the system can accurately capture significant variations in joint angles during squat movement. The observed range of motion is consistent with biomechanical studies, which report knee flexion angles between 60° and 80° during proper squat execution (Escamilla, 2001; Schoenfeld, 2010). This indicates that the proposed system produces kinematic outputs that are aligned with established biomechanical references.

4.2 Kinematic Pattern Representation

The knee joint angle trajectory over time forms a smooth and continuous curve, representing the dynamic behavior of the squat motion. The angle decreases progressively during descent, reaches a minimum at deep flexion, and increases again during ascent.

This pattern confirms that the system is capable of capturing temporal motion dynamics in a consistent manner. The smoothness of the curve also indicates that noise in landmark detection has been effectively reduced.

4.3 Stability of Noise Reduction Analysis

The application of the Exponential Moving Average (EMA) filter significantly improves the stability of the joint angle measurements. The filtered signal shows reduced fluctuations compared to raw pose estimation outputs.

However, there is a trade-off between noise reduction and responsiveness. While EMA filtering produces smoother motion curves, it may introduce slight delays in capturing rapid changes in movement. This trade-off should be considered in applications requiring high responsiveness.

The smoothness of the curve indicates that the system effectively reduces noise in pose estimation outputs. This behavior is attributed to the application of the Exponential Moving Average (EMA) filter, which stabilizes the signal while preserving the overall motion pattern. Similar filtering approaches have been widely used in motion analysis to enhance signal reliability (Hunter, 1986; Welch & Bishop, 2006).

4.4 Multi-Repetition Analysis

To further evaluate the system, multiple squat repetitions were analyzed. The results are shown in Figure 5, which presents the kinematic trajectory of the knee joint angle across several repetitions.

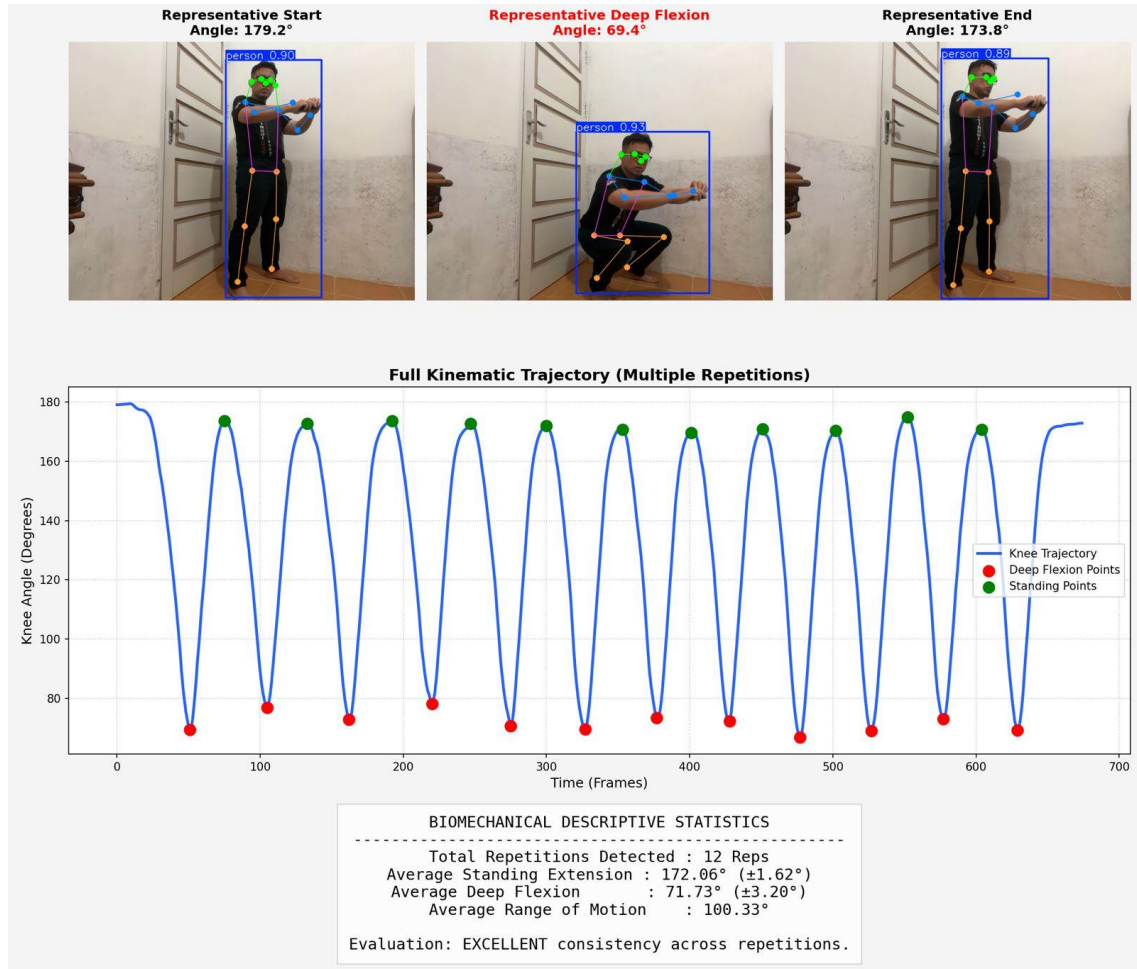


Figure 5. Kinematic trajectory of knee joint angles across multiple squat repetitions, highlighting periodic motion patterns and detected key phases (standing and deep flexion).

The graph exhibits a periodic pattern, where each cycle corresponds to one complete squat movement. The system successfully detects 12 repetitions, indicating its capability to track continuous motion over time.

The knee joint angle consistently varies between:

- 170°–175° during standing phases
- 65°–80° during deep flexion phases

Highlighted points in the graph indicate key phases:

- Green points represent standing positions
- Red points represent deep flexion positions

4.5 Statistical Analysis and Consistency

Descriptive statistical analysis was performed to evaluate movement consistency across repetitions. The results show:

- Average standing extension: 172.06° (±1.62°)
- Average deep flexion: 71.73° (±3.20°)
- Average range of motion: 100.33°

The statistical results are further illustrated in Figure 6, which shows the average knee joint angles for standing and deep flexion phases. The clear difference between the two phases confirms the system’s ability to distinguish movement states.

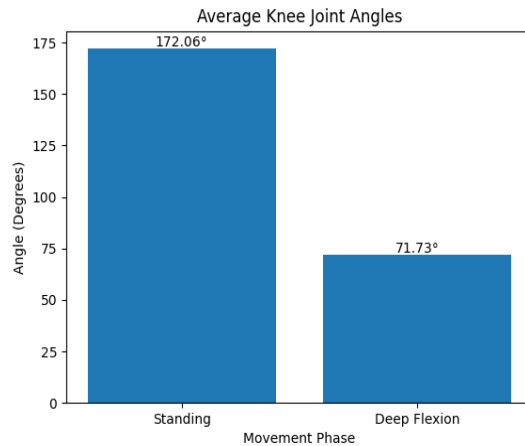


Figure 6. Average knee joint angles for standing and deep flexion phases.

The relatively low standard deviation values indicate that the motion is consistent across repetitions. These results demonstrate that the system is capable of producing stable and repeatable measurements.

4.6 Comparative Analysis with Previous Studies

The obtained results are consistent with prior biomechanical research, which reports similar joint angle ranges during squat movements (Escamilla, 2001; Schoenfeld, 2010). Compared to marker-based motion capture systems, which provide high accuracy but require controlled environments and expensive equipment (Baker, 2006; Windolf et al., 2008), the proposed system offers a more practical and low-cost alternative.

In comparison with monocular pose estimation approaches, previous studies have highlighted limitations in depth estimation and joint angle accuracy (Martinez et al., 2017; Shotton et al., 2013). The proposed system addresses this limitation by integrating vector-based mathematical modeling, which improves the interpretability and structural consistency of joint angle computation.

Furthermore, deep learning-based 3D reconstruction methods improve accuracy but require high computational resources (Dibenedetto et al., 2025; Wang et al., 2022). In contrast, the proposed system provides a balance between computational efficiency and analytical capability, making it suitable for real-time applications.

4.7 Trade-off and System Limitations

Despite its advantages, several limitations are observed. The use of the EMA filter improves signal stability but introduces a slight delay in capturing rapid motion changes, indicating a trade-off between smoothness and responsiveness.

In addition, the use of a monocular camera limits the accuracy of true three-dimensional reconstruction, particularly under suboptimal conditions such as poor lighting, occlusion, and non-ideal camera positioning. These factors may affect the robustness of pose estimation and should be considered in practical deployment.

4.8 Practical Implications

From a practical perspective, the proposed system provides a feasible solution for real-time motion analysis in home-based environments. The ability to track joint angles, detect repetitions, and evaluate movement consistency makes the system suitable for applications in fitness monitoring, exercise coaching, and basic rehabilitation.

5. Conclusion

This study presents a low-cost squat motion analysis system, *gui_mocap*, which integrates monocular pose estimation with vector-based mathematical modeling for real-time kinematic

analysis. The experimental results demonstrate that the system is capable of accurately detecting squat movements, computing knee joint angles, and analyzing repetition consistency with stable and interpretable outputs. The obtained joint angle ranges and motion patterns are consistent with established biomechanical references, indicating the reliability of the proposed approach.

The main contribution of this study lies in the development of an integrated and computationally efficient framework that combines pose estimation, geometric modeling, and signal filtering into a unified real-time system. Unlike conventional motion capture systems that require expensive hardware or complex configurations, the proposed method offers a practical and accessible solution suitable for home-based applications.

From a practical perspective, the system provides meaningful benefits for exercise monitoring, movement evaluation, and basic rehabilitation. The ability to track joint angles and assess movement consistency in real time can support users in improving exercise technique and reducing the risk of injury. These findings highlight the potential of the proposed system as a low-cost alternative for human motion analysis in real-world settings.

Future work may focus on improving system robustness under varying environmental conditions, enhancing three-dimensional motion representation, and integrating intelligent feedback mechanisms to provide personalized exercise guidance.

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