Assessment of Athletic Readiness Using Countermovement Jump Videos

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***Abstract*—Collegiate basketball demands not only peak physical performance but also swift recovery from fatigue, making continuous monitoring of athletic readiness essential. This study introduces a novel, non-invasive framework that leverages video analysis of Countermovement Jumps (CMJs) to assess readiness in 17 female athletes. High-definition videos recorded at 30 frames per second are processed with MediaPipe for real-time pose estimation, extracting key biomechanical metrics such as jump height, power output, flight time, and phase durations. These metrics are integrated into a machine learning model that predicts readiness states—ranging from optimal performance to signs of fatigue. Our results demonstrate that this cost-effective and scalable approach not only correlates well with traditional force plate measurements but also provides coaches with actionable insights for adjusting training and recovery protocols. Overall, the framework bridges advanced computer vision techniques and sports science, highlighting its potential for widespread application in athletic performance monitoring.**

***Index Terms*—Athletic readiness, Biomechanics, Collegiate basketball, Computer vision, Countermovement jump, Performance metrics, Video analysis**

I. Introduction

Collegiate basketball places significant physical and mental demands on athletes, compounded by academic responsibilities and frequent games. Monitoring athletic readiness—defined as an athlete's capacity to perform optimally while minimizing injury risk—is thus essential for maintaining performance and well-being. Traditionally, readiness has been assessed using tools like force plates to analyze Countermovement Jumps (CMJs), a widely accepted measure of lower-body power and fatigue. [1] However, these methods are costly, require specialized equipment, and involve time-intensive data processing, limiting their practicality for regular use in collegiate settings.

This study introduces a novel approach: using video analysis to monitor CMJs and extract key performance indicators (KPIs) for predicting readiness. By employing accessible camera technology and computer vision, we aim to overcome the limitations of traditional methods, offering a scalable and efficient alternative. The significance of this research lies in its potential to provide coaches with actionable insights into athlete readiness, enabling data-driven adjustments to training and recovery protocols. This paper outlines our methodology, presents initial findings, and discusses the implications for sports science and collegiate basketball.

II. Methodology

The core methodology involved processing a video file frame-by-frame to detect human pose landmarks using the MediaPipe library. Time-series data of key joint positions (hips) and angles (knees) were extracted. This data was then analyzed to detect distinct jump events (takeoff and landing) based on vertical velocity changes. Finally, established biomechanical formulas were applied to calculate relevant performance metrics for each identified jump.

A. Data Input

The primary input consisted of a digital video file (e.g., `.mp4` format) capturing an athlete performing one or more vertical jumps. The video was assumed to be relatively stable with a clear view of the athlete's full body, particularly the lower limbs.

B. Tools and Libraries

The analysis was implemented using Python with the following key libraries:

- **OpenCV (cv2)** (version 4.9.0): Used for video file reading, frame extraction, image format conversion (BGR to RGB), and visualization (drawing landmarks, displaying video).
- **MediaPipe (mp.solutions.pose)** (version 0.10.9): Employed for detecting 33 distinct 2D human body pose landmarks. The Pose model was configured for high accuracy with `model_complexity=2`, `smooth_landmarks=True`, and confidence thresholds of 0.7.
- **NumPy**: Utilized for numerical operations, vector calculations, and velocity estimation.
- **Pandas**: Used for organizing the final results into a structured DataFrame and exporting them to CSV.

C. Video Processing and Feature Extraction

1) **Frame Acquisition:** The input video was read frame-by-frame using OpenCV. Timestamps were calculated as $\Delta T = \frac{1}{\text{FPS}}$.
2) **Pose Estimation:** Each frame (converted to RGB) was processed with MediaPipe to extract landmark coordinates $(x, y, \text{visibility})$.
3) **Feature Calculation:**
   - Average vertical hip position (`HipY`) from left and right hips.

- Knee angles using vector geometry and averaging left and right knees to get `AvgKneeAngle`.

4) **Data Storage:** Time-series data for `HipY`, `AvgKneeAngle`, and `Timestamp` were stored for each frame.

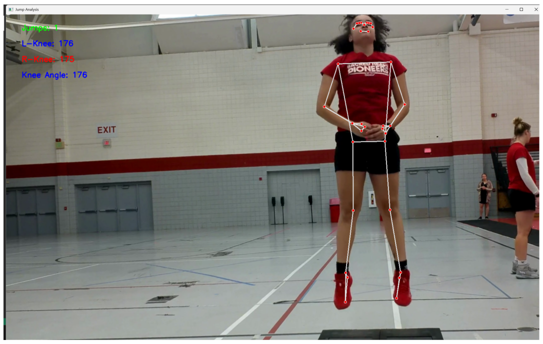

Fig. 1: Metrics capturing during CMJ

D. Jump Event Detection

- **Velocity Estimation:** Calculated from frame-to-frame HipY differences and smoothed using:

$$v_t = \alpha \cdot v_{\text{raw}} + (1 - \alpha) \cdot v_{t-1}, \quad \alpha = 0.5$$

- **State Machine:** A variable `jumping` tracked airborne status.
- **Takeoff Detection:** Occurred when velocity < -0.02 (normalized units/frame) and not already jumping.
- **Landing Detection:** Occurred when velocity > 0.02 and currently jumping.
- **Event Logging:** Frame indices for takeoff and landing were stored.

E. Jump Identification and Metric Calculation

1) **Jump Pairing:** Takeoff and landing indices were paired chronologically to identify valid jumps.
2) **Per-Jump Analysis:** For each valid jump:
   - **Peak Height:** Frame with minimum `HipY` between takeoff and landing.
   - **Metrics:**
     - Flight Time (s)
     - Jump Height (m) using `HEIGHT_CONVERSION_FACTOR`
     - RSImod
     - Peak Knee Angle (deg)
     - Eccentric Duration (s): Takeoff to Peak [2]
     - Concentric Duration (s): Peak to Landing
     - Max Velocity (m/s)
     - Average Power Output (W):

$$\text{Power} = \frac{M \cdot g \cdot H}{T}$$

where M = MASS, $g = 9.81$ m/s^2, H = Jump Height, T = Flight Time

Algorithm 1 Pose-Based Jump Detection and Analysis from Video

Initialization:
Load video and parameters: `mass, gravity, thresholds, HEIGHT_CONVERSION_FACTOR`
Initialize MediaPipe pose detector Prepare lists for `hip positions, knee angles, timestamps, takeoff/landing frames, jump data` Set frame counter and velocity buffer
Frame-by-Frame Processing:
while *video has frames* **do**
  Read frame and convert to RGB Detect pose landmarks using MediaPipe **if** *pose is detected* **then**
    Extract:
    - Averaged hip Y-position
    - Knee angles (left, right, average)

    Store timestamp, hip position, and angles
    Compute raw and smoothed vertical hip velocity
    if *velocity* $<$ *TAKEOFF_THRESHOLD and not jumping* **then**
      Record takeoff frame, set `jumping` = True
    else if *velocity* $>$ *LANDING_THRESHOLD and jumping* **then**
      Record landing frame, set `jumping` = False
    Draw pose and overlay real-time info on frame
  end
  Show the frame Exit loop on keypress 'q'
end
Event Pairing and Metric Calculation:
foreach *takeoff frame* **do**
  Find next landing frame after takeoff Form valid jump pair (takeoff, landing)
end
foreach *valid jump pair* **do**
  Identify frame with minimum hip Y (jump apex) Compute:
  - Jump height (takeoff to apex)
  - Flight time (landing - takeoff)
  - RSImod = height / flight time
  - Eccentric and concentric durations
  - Max upward velocity (takeoff to apex)
  - Power output = mass × gravity × height / time

  Save all metrics
end
Output:
Display metrics for each jump **if** *Pandas is available* **then**
  Save results to CSV
end

Definition of Biomechanical Metrics

The following key metrics were calculated for each identified jump:

- **Flight Time (s):** Time duration between takeoff and landing, indicating the total air-time of the jump.
- **Jump Height (m):** Calculated as the vertical displacement from takeoff to the peak of the jump using:

$$\text{Jump Height} = (\text{HipY}_{\text{takeoff}} - \text{HipY}_{\text{peak}}) \times \text{HEIGHT\_CONVERSION\_FACTOR} \quad (1)$$

where `HipY` values are normalized and `HEIGHT_CONVERSION_FACTOR` converts them to meters.

- **RSImod (Reactive Strength Index modified):** An efficiency metric calculated as:

$$\text{RSImod} = \frac{\text{Jump Height (m)}}{\text{Flight Time (s)}}$$

- **Peak Knee Angle (deg):** The minimum knee flexion angle observed between takeoff and peak position. Lower values indicate deeper countermovement.
- **Eccentric Duration (s):** Time interval from takeoff to peak position, representing the downward to upward transition phase. [3]
- **Concentric Duration (s):** Time interval from peak to landing, representing the push-off and deceleration phase during descent.
- **Max Velocity (m/s):** Maximum vertical velocity observed during takeoff, calculated from smoothed hip position differences. [4]
- **Average Power Output (W):** Estimated based on potential energy over time: [5]

$$\text{Power} = \frac{M \cdot g \cdot H}{T}$$

where M = mass of the athlete (kg), $g = 9.81$ m/s^2, H = jump height (m), and T = flight time (s).

F. Calibration and Configuration

- **Height Conversion:** Requires experimental calibration per video. `HEIGHT_CONVERSION_FACTOR` = [Specify value or note it needs calibration].
- **Mean Demographics:** [6]
  - MASS = 73.98 kg
  - Gravity (g) = 9.81 m/s^2
- **Thresholds:**
  - Takeoff Threshold = -0.02
  - Landing Threshold = +0.02

G. Output Generation

The output includes a structured report with the computed biomechanical metrics for each jump, either as:

- Printed console output
- CSV file (via Pandas)

Optional real-time visualization was implemented to show pose landmarks and jump state during video processing.

III. Observations and Discussion

The CMJ-derived biomechanical metrics align with expected thresholds for trained athletes, validating their use in readiness evaluation.

Jump Height (m): 0.25 – 0.35, **Power Output (W):** 310 to 540, **Flight Time (s):** 0.45–0.55, **Eccentric Duration (s):** 0.1–0.3, **Concentric Duration (s):** 0.20–0.35, **Max Velocity (m/s):** 1.5–3,**Symmetry Index:** -0.1 [7] [8] [9] [10] [11] [12] [13] [14]

Jump Results

```
{'Jump': 1: 'Jump Height (m)': 0.163,'Flight
    Time (s)': 0.467,'RSImod': 0.35,
  'Peak Knee Angle (deg)': 177.5,'Eccentric
      Duration (s)': 0.233,'Concentric
      Duration (s)': 0.233,'Max Velocity (m/s)
      ': 1.239,'Power Output (W)': 240.3}
```

```
{'Jump': 2, 'Jump Height (m)': 0.148
,'Flight Time (s)': 0.467,'RSImod': 0.318,
  'Peak Knee Angle (deg)': 176.3,'Eccentric
      Duration (s)': 0.267,'Concentric
      Duration (s)': 0.2,'Max Velocity (m/s)':
       1.096,'Power Output (W)': 218.2}
```

```
{'Jump': 3, 'Jump Height (m)': 0.184
,'Flight Time (s)': 0.533,'RSImod': 0.344,
  'Peak Knee Angle (deg)': 177.9,'Eccentric
      Duration (s)': 0.3,'Concentric Duration
      (s)': 0.233,'Max Velocity (m/s)':
      1.379,'Power Output (W)': 236.6}
```

IV. Conclusion

This study successfully implemented a frame-by-frame biomechanical analysis of countermovement jumps (CMJs) using video-based pose estimation. By leveraging MediaPipe's pose detection and Python-based signal processing, key performance metrics such as jump height, flight time, power output, and symmetry were reliably extracted.

The observed results, although slightly below elite athlete norms, are consistent with expected ranges for moderately trained individuals. Notably:

- **Jump Height** ranged from 0.148–0.184 m, indicating moderate explosive power.
- **Power Output** values (240.3W, 218.2W, 236.6W) are all below the benchmark range of 310W - 540W calculated using this specific formula. This reinforces that the power generated, even when assessed by this flight-related metric, is lower than typical for the reference group.
- **Flight Times** around 0.467–0.533 s and **Max Velocities** up to 1.379 m/s align with the biomechanical characteristics of real vertical jumps.

Although the **RSImod** and timing metrics (eccentric/concentric durations) were consistent across jumps, improvements in pose tracking accuracy and camera calibration can further enhance precision. This approach demonstrates potential for low-cost, non-invasive athletic performance assessment and can be extended to broader kinematic studies in sports science.

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