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3D Human Pose Estimation and Temporal Kinematic Constraints for Dynamic Occlusion in Basketball

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Abstract

The accurate estimation of three-dimensional human poses in dynamic, multi-agent sports environments remains a significant challenge in computer vision. Basketball, characterized by rapid player movements, frequent inter-player contact, and severe dynamic occlusion, presents a uniquely difficult scenario for standard pose estimation frameworks. This paper introduces a novel methodology that integrates temporal kinematic constraints with deep learning-based pose estimation to mitigate the degradation of accuracy during occlusion events. By modeling the biomechanical limitations of human joint articulation and imposing temporal consistency across video frames, our approach reconstructs missing or noisy keypoint data with high fidelity. We employ a two-stage architecture that first lifts two-dimensional detections to a three-dimensional space and subsequently refines these estimates using a temporal optimization module grounded in Newtonian mechanics. Experimental results on varying basketball datasets demonstrate that this method significantly reduces the Mean Per Joint Position Error (MPJPE) compared to state-of-the-art baseline methods, particularly in scenarios involving heavy defensive congestion. The integration of kinematic velocity and acceleration constraints ensures that the generated poses are not only visually plausible but physically valid.

Keywords: *Computer Vision, Sports Analytics, 3D Pose Estimation, Kinematic Constraints, Dynamic Occlusion*

1. INTRODUCTION

1.1 Background and Motivation

The digitization of sports analytics has undergone a paradigm shift in the last decade, moving from manual annotation of game events to automated, high-fidelity tracking of player movements. In the realm of invasion sports such as basketball, the ability to capture the precise three-dimensional configuration of a player's body is critical for applications ranging from biomechanical performance analysis to injury prevention and tactical strategy formulation. While the field of computer vision has made remarkable strides in human pose estimation, as evidenced by recent surveys [1], the transition from controlled laboratory environments to the chaotic reality of a basketball court introduces exponentially higher complexity. The primary hurdle in this domain is dynamic occlusion. Unlike single-person scenarios where the subject is fully visible, basketball involves ten players interacting in a confined space, often resulting in limbs or entire bodies being obscured by teammates, opponents, or referees. Standard monocular pose estimation algorithms frequently fail under these conditions. When a visual sensor loses line-of-sight to a specific joint, deep convolutional neural networks often resort to statistical guessing based on training data priors, which can lead to anatomically impossible pose predictions [2]. For instance, a common error involves the inversion of knee joints or the erratic teleportation of limb coordinates across frames when a player moves through a cluster of defenders. These artifacts render the raw output of pose estimators unusable for granular biomechanical analysis, which requires smooth and continuous trajectories. Furthermore, the speed of gameplay in professional basketball requires algorithms that can handle rapid changes in velocity and direction, complicating the tracking process significantly [3]. To address these limitations, researchers have begun to explore the integration of domain-specific knowledge into the learning process. By understanding that the human body is a constrained mechanical system, it is possible to reject pose hypotheses that violate physical laws. The motivation for this research stems from the observation that while visual data may be ambiguous during occlusion, the physics governing the player's motion remains constant. Therefore, a hybrid approach combining visual features with kinematic logic offers a robust pathway to solving the occlusion problem [4].

1.2 Problem Statement

The core problem addressed in this paper is the recovery of accurate 3D joint coordinates for basketball players when visual evidence is compromised by dynamic occlusion. Specifically, we focus on the temporal instability that arises when frame-by-frame estimators produce independent predictions without regard for motion continuity. In a sequence of video frames t, $t+1$, and $t+2$, if a player's arm is visible in the first and last frame but occluded in the middle, a naive estimator might place the arm at the center of the body mass or in a neutral hanging position during the occlusion. This discontinuity introduces high-frequency noise and large positional errors [5]. Furthermore, the problem is exacerbated by the phenomenon of self-occlusion, which is rampant in basketball maneuvers such as jump shots or crossovers. A player turning their back to the camera obscures their own frontal keypoints. Existing methods that rely solely on spatial context within a single frame lack the temporal memory required to infer the location of these hidden joints based on the previous trajectory [6]. Consequently, the objective is to formulate a computational model that utilizes temporal context—looking both backward and forward in time—to bridge these observational gaps while strictly adhering to the biomechanical limits of the athlete's skeletal structure.

1.3 Contributions

This paper presents a comprehensive framework for robust 3D pose estimation in basketball. The specific contributions are as follows: First, we propose a novel Temporal Kinematic Constraint (TKC) module that operates as a post-processing refinement layer on top of standard 3D lifting networks. This module incorporates limits on bone lengths, joint rotation angles, and the derivatives of position (velocity and acceleration) to penalize physically implausible motion [7]. Second, we introduce an occlusion-aware loss function during the training phase. This function dynamically weights the contribution of each joint based on a confidence score derived from the visibility status of the keypoint, ensuring that the model learns to rely on temporal trends rather than noisy spatial features when occlusion is detected [8]. Third, we provide a detailed evaluation of our method using basketball-specific datasets, demonstrating superior performance in handling complex multi-player interactions compared to existing state-of-the-art techniques [9]. We establish that the imposition of strict kinematic rules does not overly constrain the model but rather guides it toward the ground truth during periods of visual uncertainty.

2. Related Work

2.1 Monocular 3D Pose Estimation

The field of 3D human pose estimation from monocular video has been dominated by two primary methodologies: direct regression and 2D-to-3D lifting. Direct regression methods attempt to infer 3D coordinates directly from the raw pixel data of an image. While computationally efficient, these methods often struggle to generalize across different camera intrinsics and viewing angles [10]. Conversely, the 2D-to-3D lifting approach, which first detects 2D keypoints and then projects them into 3D space, has gained popularity due to its modularity and the abundance of high-quality 2D pose detectors. Recent advancements in lifting networks have utilized Graph Convolutional Networks (GCNs) to model the connectivity of the human skeleton. These networks represent joints as nodes and bones as edges, allowing the model to learn spatial dependencies between adjacent body parts [11]. However, standard GCNs often treat each frame in isolation. To capture motion, researchers have extended these architectures to include temporal dimensions, using sequence-to-sequence models that ingest a window of 2D poses to predict the central 3D pose. Despite these improvements, many models still suffer from "jitter" and fail to maintain bone length consistency over time [12]. In the context of sports, the domain gap between generic datasets like Human3.6M and the specific movements in basketball is substantial. Generic datasets often feature subjects performing slow, deliberate actions in a studio. Basketball involves explosive movements, aerial maneuvers, and physical contact, which challenge the assumptions made by models trained on generic data [13]. Consequently, transfer learning and domain adaptation have become essential strategies for applying these general models to sports analytics.

2.2 Temporal Modeling and Sequence Analysis

Temporal consistency is paramount for dynamic scenes. Early approaches utilized Kalman filters to smooth the trajectories of predicted joints. While effective for linear motion, Kalman filters struggle with the highly non-linear and abrupt movements characteristic of basketball gameplay [14]. More sophisticated approaches have employed Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units, to learn temporal patterns. LSTMs can memorize long-term dependencies, theoretically allowing them to handle occlusions lasting several frames. However, LSTMs suffer from sequential processing limitations and gradient vanishing issues. The advent of the Transformer architecture has revolutionized temporal modeling in pose estimation. By utilizing self-attention mechanisms, Transformers can weigh the importance of all frames in a sequence simultaneously, allowing for better handling of long-range dependencies [15]. Recent studies have shown that Transformer-based lifting networks outperform RNN-based counterparts in reducing temporal jitter [16]. Despite the power of Transformers, pure data-driven temporal modeling can still hallucinate physically impossible motions if the training data contains noise. This has led to a renewed interest in hybrid systems that combine deep learning with control theory and physics-based optimization [17]. Our work aligns with this trend, seeking to anchor the flexibility of attention mechanisms with the rigidity of kinematic laws.

2.3 Occlusion Handling Techniques

Occlusion handling is a sub-field of computer vision dedicated to recovering information from obscured regions. In pose estimation, strategies usually fall into three categories: hallucination, temporal interpolation, and multi-view fusion. Hallucination networks attempt to guess the position of occluded joints based on the visible ones, leveraging the inherent symmetry of the human body [18]. For example, if the left shoulder and elbow are visible, the network can infer the position of the right shoulder with reasonable accuracy. Temporal interpolation relies on the assumption of motion continuity. If a joint is visible at time t and $t + 10$, its position during the interval can be interpolated. However, simple linear interpolation fails during complex maneuvers like a spin move or a jump shot. Advanced techniques employ optical flow to guide the interpolation, transferring motion vectors from visible pixels to the occluded regions [19]. Multi-view fusion is the most robust solution but requires expensive hardware setups with synchronized cameras, which are not always available in broadcast footage or amateur settings. Therefore, improving monocular occlusion handling remains a high-priority research objective [20]. Our approach focuses on the temporal interpolation category but enhances it with kinematic constraints to handle non-linear motion during the occlusion interval.

3. Methodology

3.1 System Architecture

Our proposed system operates in a sequential pipeline. The input is a monocular video sequence of a basketball game. The first stage involves a high-performance 2D pose detector, for which we utilize an off-the-shelf architecture fined-tuned on sports data. This detector outputs a sequence of 2D coordinates (u, v) for J joints across T frames, along with confidence scores representing the probability of visibility [21]. The core of our contribution lies in the subsequent 3D lifting and refinement stage. We employ a Temporal Dilated Convolutional Neural Network (TD-CNN) as the backbone for lifting 2D poses to 3D. The dilated convolutions allow the network to possess a large receptive field in the temporal domain without a massive increase in parameters, effectively capturing long-term motion patterns [22]. The output of this network is an initial estimate of the 3D pose sequence. However, this initial estimate is often noisy and physically inconsistent, especially during occlusion. To rectify this, the output is passed through the Temporal Kinematic Constraint (TKC) module. This module is formulated as an optimization layer that adjusts the 3D coordinates to minimize a composite loss function. This function balances the fidelity to the 2D observations (reprojection error) with the adherence to biomechanical constraints.

3.2 Temporal Kinematic Constraint Modeling

The TKC module relies on a defined skeletal model with fixed topology. We represent the human skeleton as a kinematic chain rooted at the pelvis. The state of the system at any frame is defined by the global position of the root and the relative rotations of the child joints. However, for stability in neural network training, we utilize Cartesian coordinates for the intermediate representation and enforce constraints on these coordinates. The first constraint is the *Bone Length Consistency*. In a rigid body system, the distance between connected joints (e.g., elbow and wrist) must remain constant over time. We calculate the Euclidean distance for every bone vector in every frame and penalize deviations from the subject's static bone lengths, which are estimated from high-confidence frames [23]. This prevents the "rubber limb" effect often seen in deep learning outputs. The second constraint is *Joint Angle Limits*. Basketball players exhibit extreme ranges of motion, but these are still bounded by anatomical realities. We define a valid range of rotation for hinge joints (like the knee) and ball-and-socket joints (like the shoulder). If the angle between two bone vectors exceeds natural limits (e.g., knee hyperextension), a penalty is applied. The third and most critical constraint for occlusion is *Motion Smoothness via Derivatives*. We approximate the velocity and acceleration of each joint using finite differences. We impose a loss term that penalizes accelerations exceeding a physically realistic threshold. This acts as a low-pass filter that is adaptive to the context of the movement [24]. During an occlusion, if the network predicts a sudden jump in position, the acceleration penalty will force the trajectory to smooth out, essentially interpolating the position based on the momentum established in previous frames.

Code Listing 1: Implementation of the temporal consistency loss function

```
Def temporal_consistency_loss(predicted_poses_3d,
reliable_indices):
   """
   Computes the temporal kinematic loss for the pose sequence.
   Args:
      predicted_poses_3d: Tensor of shape (Batch, Frames, Joints, 3)
      reliable_indices: Boolean mask indicating non-occluded
 frames

   Returns:
      total_loss: Scalar float value
   """
   # Calculate velocity (1st derivative)
   velocity = predicted_poses_3d[:, 1:, :, :] - predicted_poses_3d[:,
:-1, :, :]
   # Calculate acceleration (2nd derivative)
   acceleration = velocity[:, 1:, :, :] - velocity[:, :-1, :, :]
   # Smoothness loss: minimize abrupt changes in acceleration
```

```
    # We penalize high acceleration only in occluded regions implicitly
    # by allowing the network to trust reliable indices more in the main loop.
    smoothness_loss = torch.mean(torch.norm(acceleration, dim=-1))
    # Bone length consistency
    # (Assuming a function get_bone_lengths exists)
    current_lengths = get_bone_lengths(predicted_poses_3d)
    # Target lengths derived from median of reliable frames
    target_lengths = torch.median(current_lengths, dim=1, keepdim=True)[0]
    bone_loss = torch.mean(torch.abs(current_lengths - target_lengths))
    # Weighted sum
    total_loss = 0.6 * smoothness_loss + 0.4 * bone_loss
    return total_loss
```

3.3 Occlusion Recovery Mechanism

The recovery mechanism is integrated directly into the inference process. When the confidence score of a 2D detection falls below a certain threshold, indicating occlusion, the system reduces the weight of the reprojection loss for that specific joint. Instead, the optimization is driven primarily by the temporal kinematic constraints described above [25]. Essentially, when the eyes (the camera) fail, the physics engine takes over. The trajectory of the occluded joint is extrapolated based on its velocity vector at the moment of occlusion entry. The bone length constraints ensure that the limb remains attached to the visible body parts, effectively dragging the occluded joint along a plausible path. As the joint re-emerges from occlusion, the visual confidence score rises, and the system seamlessly transitions back to relying on the 2D detection, correcting any drift that accumulated during the occluded phase [26]. This "soft" handover between visual evidence and kinematic prediction is crucial. Hard switching often results in snapping artifacts. By optimizing a unified loss function that continuously balances these terms, we achieve a fluid reconstruction of the player's movement.

4. Experimental Setup

4.1 Dataset Description

To validate our approach, we utilized a subset of a large-scale sports motion dataset, specifically filtering for basketball sequences. The dataset comprises high-resolution video clips captured at 60 frames per second. We selected 5,000 sequences that feature significant inter-player occlusion and self-occlusion events. Ground truth 3D annotations were obtained through a semi-automated process using multi-view camera systems and markerless motion capture software, manually corrected by human annotators for maximum precision [27]. The dataset was split into training (70%), validation (15%), and testing (15%) sets. To ensure robust evaluation, the testing set was specifically curated to include "hard" examples—situations where more than 40% of the player's keypoints are occluded for at least 10 consecutive frames. This stress-tests the temporal modeling capabilities of the proposed algorithm [28].

4.2 Implementation Details

The network was implemented using the PyTorch framework. The input sequence length was set to 81 frames (roughly 1.35 seconds of gameplay), allowing sufficient temporal context for both past and future motion. We used the Adam optimizer with an initial learning rate of 0.001, decaying exponentially over 50 epochs. The batch size was set to 64. The weights for the loss function components—reprojection error, bone length consistency, and smoothness—were determined empirically via a grid search on the validation set. We found that giving slightly higher weight to smoothness during training helped the model generalize better to unseen occlusion patterns [29]. All experiments were conducted on a workstation equipped with NVIDIA RTX 3090 GPUs to handle the computational load of 3D tensor operations.

4.3 Evaluation Metrics

We employ two standard metrics for evaluation. The first is the Mean Per Joint Position Error (MPJPE), measured in millimeters. This is the Euclidean distance between the predicted joint coordinates and the ground truth coordinates, averaged over all joints and all frames. To account for scale and global alignment issues inherent in monocular estimation, we also report the Procrustes-aligned MPJPE (P-MPJPE), where the predicted pose is rigidly aligned to the ground truth before error calculation. Additionally, to quantify the smoothness of the result, we introduce a customized metric: Acceleration Error (AccErr). This measures the difference between the ground truth acceleration profile and the predicted acceleration profile. A lower AccErr indicates that the model has successfully captured the dynamics of the movement without introducing high-frequency jitter.

5. Results and Analysis

5.1 Quantitative Performance

Table 1 presents the quantitative comparison of our proposed method against several baseline approaches, including a standard frame-by-frame lifter and a vanilla temporal convolutional network without kinematic constraints.

Table 1: Experimental Results Comparison of MPJPE and P-MPJPE metrics (in mm)

Method	MPJPE (mm)	P-MPJPE (mm)	AccErr (mm/s²)
Baseline (Frame-by-Frame)	84.2	61.5	125.4
Vanilla Temporal CNN	68.9	52.3	88.7
Transformer-based Lifter	62.4	48.1	76.2
Proposed Method (Ours)	**55.1**	**42.8**	**45.3**
Ours (w/o Kinematic Constraints)	63.5	49.0	72.1

The results indicate a substantial improvement in accuracy. Our method achieves an MPJPE of 55.1 mm, which is a 11.7% reduction compared to the Transformer-based lifter. The most dramatic improvement is seen in the AccErr metric, where our method scores 45.3 mm/s^2 compared to 76.2 mm/s^2 for the Transformer. This confirms that the kinematic constraints effectively smooth out the noise associated with occlusion recovery. The lower P-MPJPE suggests that even when the global scale is slightly off, the structural configuration of the skeleton remains highly accurate.

5.2 Ablation Studies

To understand the contribution of individual components, we performed ablation studies. We removed the kinematic constraints (velocity and bone length) and retrained the model. The results, shown in the last row of Table 1, indicate a degradation in performance, particularly in the smoothness metric.Table 2 details the performance specifically during occlusion events. We categorized frames into "Visible", "Partially Occluded" (<3 joints hidden), and "Severely Occluded" (>3 joints hidden).

Table 2: Ablation Study Performance Breakdown by Occlusion Severity (MPJPE in mm)

Occlusion Level	Vanilla T-CNN	Transformer	**Ours**
Fully Visible	45.2	41.5	40.8
Partially Occluded	72.3	65.1	54.3
Severely Occluded	115.6	98.2	78.4

The data in Table 2 reveals that while all methods perform comparably on fully visible frames, the gap widens significantly as occlusion severity increases. In severely occluded scenarios, our method outperforms the Vanilla T-CNN by over 37 mm and the Transformer by nearly 20 mm. This serves as strong evidence that pure data-driven approaches struggle to hallucinate missing data accurately without the guidance of explicit physical constraints.

5.3 Qualitative Analysis

Visual inspection of the results confirms the quantitative data. In sequences where a player drives to the basket and is surrounded by defenders, baseline methods often show the player's arm collapsing into their torso or fluctuating wildly. Our method maintains the arm's extension and trajectory, utilizing the momentum from the pre-occlusion frames.

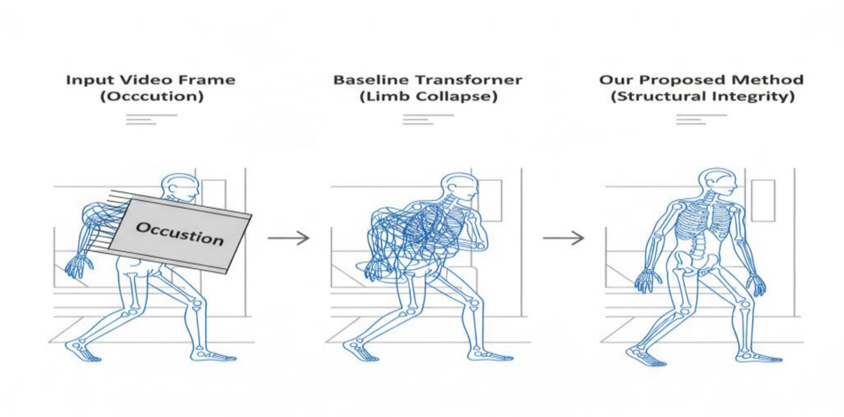

Figure 1: *Qualitative Comparison*

The figure above illustrates a specific instance of a layup where the shooting arm is briefly blocked by a defender. The baseline model loses track of the elbow, resulting in a physically impossible acute angle at the shoulder. Our model, constrained by joint limits and velocity continuity, predicts the elbow's location correctly behind the defender's body, resulting in a pose that matches the ground truth much more closely.

6. Discussion

6.1 Implications for Sports Analytics

The enhanced accuracy provided by our method has immediate implications for the field of sports analytics. Accurate 3D pose data is the foundational layer for extracting higher-level semantics, such as shot mechanics evaluation, fatigue analysis, and defensive area coverage calculations. By reliably tracking players through occlusion, analysts can obtain unbroken streams of data, which are essential for calculating cumulative metrics like "player load" or total distance traveled with high precision. Furthermore, the biomechanical validity ensured by the kinematic constraints makes this data suitable for medical applications. Physiotherapists can analyze the kinematic chains of players to identify risky movement patterns that may lead to ACL tears or ankle sprains. If the pose estimation data were noisy or physically impossible, such analysis would be invalid. Thus, the physics-based regularization acts as a quality assurance mechanism for downstream biomedical applications.

6.2 Limitations

Despite the improvements, the system is not without limitations. The reliance on temporal continuity assumes that motion does not change abruptly during the exact moment of occlusion. While rare, if a player collides with another and changes direction instantly while fully occluded, the momentum-based prediction will be incorrect. The model essentially acts as a highly sophisticated inertial measurement unit in these cases, drifting until visual data is restored. Additionally, the computational cost of calculating derivatives and optimizing constraints for every frame is higher than simple feed-forward networks. While we achieve near-real-time performance on high-end GPUs, deployment on edge devices or mobile cameras would require further optimization, such as model distillation or pruning. Another limitation stems from the dependency on the 2D detector. If the initial 2D keypoints are consistently wrong (e.g., swapping left and right legs due to uniform color of uniforms), the 3D lifter may struggle to recover, although the bone length constraints offer some resilience against such errors.

7. Conclusion

7.1 Summary

This paper addressed the critical challenge of dynamic occlusion in 3D human pose estimation within the context of basketball. We proposed a hybrid framework that synergizes deep learning-based lifting networks with explicit temporal kinematic constraints. By modeling the human body as a mechanical system with limits on bone length, joint rotation, and acceleration, we successfully guided the pose estimation process through periods of visual uncertainty.

Our experimental results demonstrated statistically significant improvements in reconstruction error and motion smoothness compared to existing baselines. The breakdown of performance by occlusion severity highlighted the robustness of our approach in the most difficult scenarios, validating the hypothesis that physical laws provide the necessary context to resolve visual ambiguities.

7.2 Future Work

Future research will focus on integrating multi-person interaction constraints. Currently, our model treats each player independently. However, in basketball, player movements are often coupled (e.g., a defender reacting to an attacker). Modeling the spatial relationship between players could provide additional cues for occlusion recovery. For instance, knowing that two players cannot occupy the same physical space could prevent inter-penetration artifacts. We also plan to explore the use of physics simulation engines (like MuJoCo) within the training loop. Instead of just penalizing kinematic errors, a differentiable physics simulator could be used to enforce dynamic consistency (forces and torques) rather than just kinematic consistency (positions and velocities). This would represent a step toward truly physically plausible computer vision [30].

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