Player Tracking Methodology

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1 Technical Approach

1.1 Core Architecture

- **Two-Stage Pipeline**:
  - Detection: YOLOv8 model (custom-trained)
  - Tracking: Hybrid feature+appearance matching
- **Key Components**:
  - SIFT feature extraction
  - Bounding box IoU matching
  - Temporal consistency checks

1.2 Implemented Techniques

1. **Baseline Method**:
   - Simple IoU-based tracking
   - Failed during occlusions (ID switches)
2. **Improved Version**:
   - Added SIFT feature matching (30% improvement)
   - Aspect ratio similarity metric
   - Frame history buffer (reduced ID switches by 45%)
3. **Final Approach**:
   - Weighted similarity score:
     - 60% IoU
     - 20% aspect ratio
     - 20% SIFT features
   - Temporal window of 30 frames

2 Performance Metrics

3 Key Challenges

3.1 Occlusion Handling

- Implemented feature caching
- Added trajectory prediction

Table 1: Tracking Performance Comparison

Method	MOTA ↑	ID Switches ↓	FPS
Baseline	0.62	87	28
Feature-Augment	0.78	48	22
Final	0.85	26	18

3.2 Real-Time Constraints

- Optimized SIFT extraction ROI
- Implemented frame skipping

3.3 Lighting Variations

- Added histogram equalization
- Normalized feature descriptors

4 Lessons Learned

4.1 Critical Findings

- Appearance features degrade rapidly in sports videos
- Simple geometric metrics often outperform complex features
- 60-80 frame buffer optimal for this use case

4.2 Unexpected Results

- Color histograms hurt performance
- Smaller players tracked more reliably than larger ones

5 Future Improvements

5.1 Near-Term

- Implement DeepSORT integration
- Add team classification

5.2 Long-Term

- End-to-end trainable tracker
- 3D position estimation