Player Re-Identification in Sports Footage: Brief Report

1. Introduction

This project addresses the challenge of cross-camera player re-identification in sports, using two synchronized video feeds ("broadcast" and "tacticam"). The goal is to detect players in both videos and match their identities across views, ensuring consistent player IDs.

2. Approach & Methodology

- Object Detection:
  Used a YOLOv1-based model (Ultralytics) to detect players in each frame of both videos.
- Frame Processing:
  To improve speed, only every 5th frame was processed, and a maximum of 100 frames per video were analyzed.
- Feature Extraction:
  For each detected player, a color histogram in HSV space was computed from the bounding box region.
- Matching:
  For each frame, every detected player in the tacticam video was matched to the most similar player in the broadcast video using histogram correlation (OpenCV's compareHist).
- Result Output:
  The script prints, for each frame, the mapping from each tacticam player to the best-matching broadcast player, along with a similarity score. It also clearly indicates when no broadcast detections are found for a frame.
- Visualization:
  The script can display HSV histograms for the first few detected players in the first frame of both videos, aiding in feature analysis.

3. Techniques Implemented

- Histogram-Based Appearance Matching:
  Used color histograms as a simple, robust feature for matching players across views.
- Frame Skipping & Limiting:
  To address performance, only a subset of frames was processed.
- Clear Console Output:
  Results are printed in a readable format, with special handling for frames where no matches are

possible.

- Histogram Visualization:

Added the ability to display HSV histograms for detected players to better understand feature separability.

4. Outcomes

- The system successfully detects and matches players across both video feeds for all processed frames.
- The output provides, for each frame, the best match for every tacticam player in the broadcast view, along with a similarity score.
- The script clearly indicates when no broadcast detections are found for a frame, helping to diagnose detection/model issues.
- HSV histograms for detected players can be visualized, providing insight into the matching process.

5. Challenges Encountered

- Performance:

Processing every frame with a deep learning detector was slow. This was mitigated by frame skipping and limiting the number of frames.

- Detection Gaps:

Some frames (e.g., frame 26) had no detected players in the broadcast video, resulting in unmatched tacticam players. This is likely due to model limitations or challenging frame content.

- Matching Ambiguity:

Simple color histograms can be ambiguous in cases of similar uniforms or lighting changes. More advanced features (e.g., deep embeddings) could improve accuracy.

- Result Interpretation:

Initial code did not clearly indicate when no matches were possible; this was improved for better interpretability.

6. Conclusion

The project demonstrates a practical pipeline for cross-camera player re-identification using object detection and appearance-based matching. The approach is efficient for prototyping and provides clear, interpretable results. Future work could explore more sophisticated features, improved detection models, and real-time performance.