GameTheory : Assignment Report

Ideas and Thought Process for Solving the Task

When approaching the player segregation task, my primary goal was to develop a solution that could efficiently and accurately classify player images without relying on pre-labelled data. This challenge required careful consideration of various factors and techniques. Here is an overview of my thought process:

1. **Problem Analysis**: The task involved unlabelled images from two court halves, requiring a solution that runs in under 2 minutes. Given the absence of labelled data, I opted for an unsupervised learning approach.

2. **Method Exploration**: I considered a range of methods, from simple colour-based clustering to advanced deep learning, with a focus on accuracy, speed, and efficiency.

3. **Computer Vision Techniques**: The task's visual nature led me to explore traditional CV methods (e.g., colour histograms, edge detection) alongside deep learning approaches.

4. **Balancing Complexity and Speed**: To meet the 2-minute runtime, I considered pre-trained models for quick feature extraction without extensive training time.

5. **Challenges**: I anticipated difficulties from varying player poses, similar clothing colours, and the court background, shaping my feature extraction and clustering choices.

6. **Iterative Refinement**: I started with simple colour and edge-based features, refining my method to incorporate deep learning features based on performance.

7. **Scalability**: I designed the solution to scale for more players or different court setups beyond the initial four-player scenario.

8. **Real-world Applicability**: I ensured the solution was suited for real-time use, influencing my algorithm and implementation choices.

This thought process led me to my approach: using a pre-trained ResNet model for feature extraction followed by K-means clustering. This method balances the need for sophisticated feature representation with computational efficiency, while adhering to the unsupervised nature of the task.

Approach 0 : Preliminary Experiment: Clustering without ResNet

Before implementing the full approach with a pre-trained ResNet model, **I conducted** a preliminary experiment using simpler feature extraction techniques. This experiment aimed to establish a baseline and understand the challenges involved in clustering the player images.

In this preliminary experiment, I used the following steps:

1. **Colour Histogram:** Extract colour histograms from each image to capture the distribution of colours.
2. **Feature Combination:** Combine the colour and edge features into a single feature vector for each image.
3. **K-means Clustering:** Use the K-means algorithm to cluster the images based on these combined features.

Results and Observations:

- The preliminary approach showed some success in grouping similar images together, particularly when players had distinct clothing colors.

Challenges:

- Pose variations: Different player poses led to inconsistent edge features, affecting clustering quality.
- Sensitivity to background: The court's background color often dominated the features, making it difficult to distinguish between players.
- Lack of semantic understanding: Simple color and edge features failed to capture higher-level semantic information about the players.

These observations led me to conclude that a more sophisticated feature extraction method was necessary, prompting the use of a pre-trained deep learning model in our final approach.

Approach 1: Using Clustering to Segregate the Data

Overview

The first approach we considered for segregating the player images involves using unsupervised clustering techniques. This method is particularly suitable for my scenario, as I am dealing with unlabelled data and need to group similar images together without prior knowledge of player identities.

The core idea behind this approach is to extract meaningful features from each image and then use these features to group the images into clusters, where each cluster represents a distinct player. Here is a brief overview of the steps involved:

1. **Feature Extraction:** Utilize a pre-trained deep learning model (e.g., ResNet) to extract high-level features from each image.
2. **Clustering:** Apply a clustering algorithm (e.g., K-means) to group the images based on their feature representations.
3. **Segregation:** Assign each image to its corresponding player folder based on the clustering results.

Clustering with ResNet Features

Based on the insights gained from the preliminary experiment, I implemented the clustering approach using features extracted from a pre-trained ResNet-18 model. This approach leverages the power of deep learning to capture more meaningful and robust features from the player images.

Key components of the implementation:

1. **Feature Extraction:**
   - Utilize a pre-trained ResNet-18 model, removing the final classification layer. Pass each image through the modified ResNet to obtain a 512-dimensional feature vector.
2. **Clustering:**
   - Apply K-means clustering on the extracted features, setting K=2 for each court half (top and bottom). This results in four clusters total, corresponding to the four players.

3. **Image Segregation:**
    - Assign each image to one of four output folders based on its cluster assignment.

Advantages:

- Unsupervised: No need for manual labelling of training data.
- Robust Features: Deep learning features capture high-level semantic information about players.
- Efficiency: ResNet feature extraction is relatively fast, allowing for real-time processing.

Challenges:

- Cluster Consistency: Ensuring consistent player assignments across different game frames.
- Optimal Cluster Number: Determining the right number of clusters if the number of players is unknown.
- Background Influence: Mitigating the impact of the court background on player clustering.

Approach 2: Manually Labelling Data and Training a Classification Model

Overview

An alternative approach to player segregation involves manually labelling a subset of the data and training a supervised classification model. While this method can potentially yield high accuracy, it is important to note that it may not strictly adhere to the problem statement's guidelines, which imply working with unlabelled data.

The steps for this approach would include:

1. Data Labelling: Manually assign player labels to a subset of images from each court half.
2. Model Architecture: Design or select a suitable convolutional neural network (CNN) architecture for player classification.
3. Training: Train the CNN on the labelled dataset, using techniques like data augmentation to improve generalization.
4. Segregation: Sort the images into player-specific folders based on the model's predictions.

Advantages:

- High Accuracy: Supervised learning often yields more accurate results than unsupervised methods.
- Interpretability: The model's performance can be quantitatively evaluated on a held-out test set.

Challenges:

- Labor-Intensive: Requires manual labelling effort, which can be time-consuming.
- Potential Overfitting: Risk of the model memorizing specific player appearances rather than generalizing.

Compliance with Problem Statement

It is crucial to highlight that this supervised approach may not align with the spirit of the original problem statement, which presents the task as an unsupervised learning challenge. The assignment specifically provides unlabelled data in two folders (top_two_players and bot_two_players), suggesting that a solution should be developed without relying on manually labelled training data.

For this reason, I have not pursued or implemented this supervised approach in my solutions. Instead, I focused on the clustering-based method described earlier, which better aligns with the unsupervised nature of the problem and the provided dataset structure.

Conclusion

In this report, I have presented three potential approaches to the player segregation problem: an unsupervised clustering method and a supervised classification approach. I have chosen to implement the clustering-based solution using ResNet features, as it best addresses the requirements and constraints of the assignment. This method allows me to efficiently segregate player images without the need for manual labelling, making it suitable for real-time applications and adhering to the spirit of the problem statement.

My thought process and exploration of different ideas led me to a solution that balances accuracy, efficiency, and adherence to the problem constraints. By leveraging deep learning features and unsupervised clustering, I have developed a method that can potentially be applied to various player segregation scenarios in badminton and possibly other sports.