Automatic analysis of ball possessions in soccer games

Computer Vision

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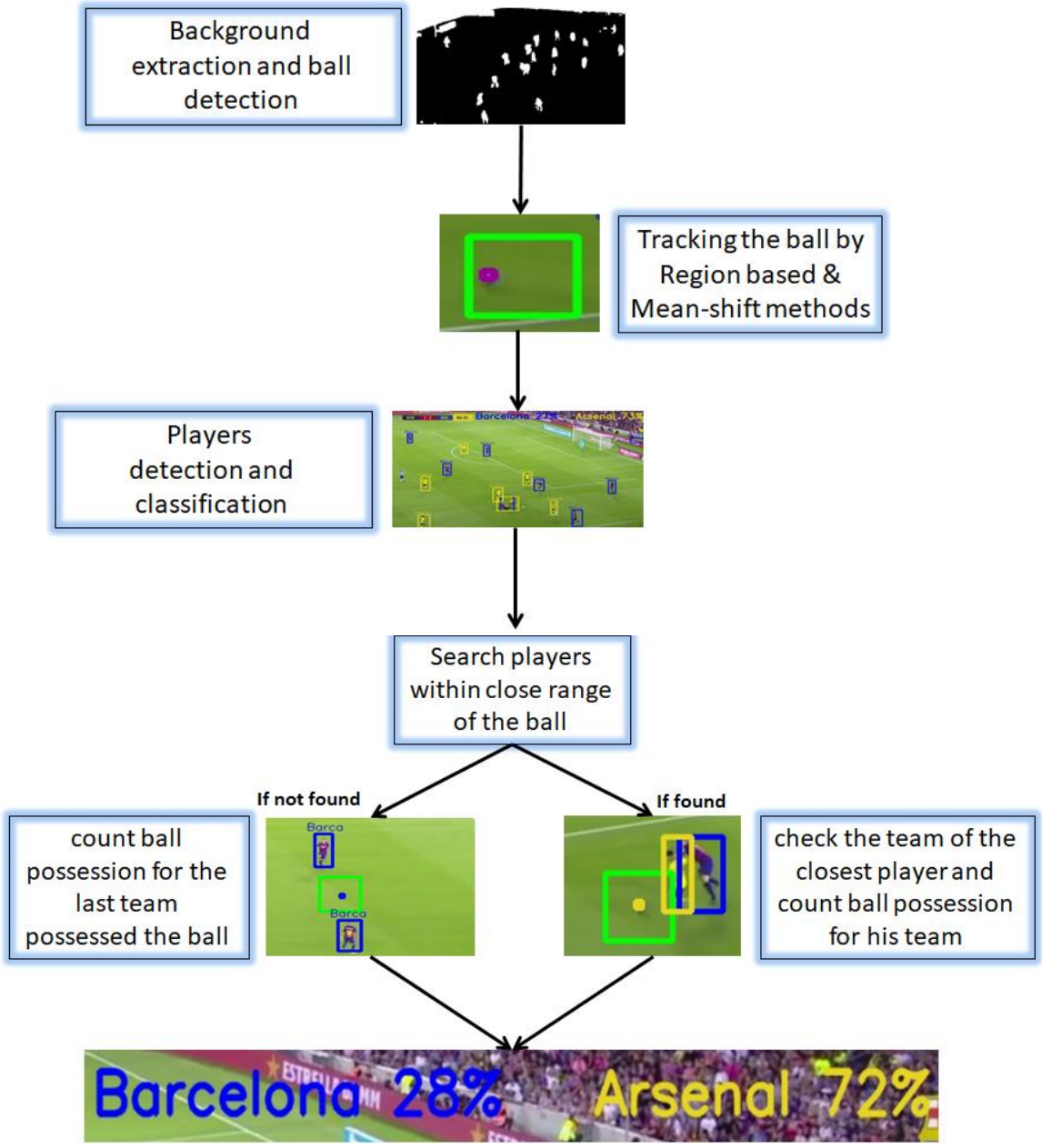
Introduction:
Nowadays soccer ball possession is computed manually by the sum of passes for each team divided by the game total passes to produce a percentage of ball possession.
This method has been found correlated with the actual ball possession of most games but not in teams that make a lot of passes during the game like Barcelona.
In this project, we are trying to measure it automatically by classifying which team possesses the ball in each frame, based on computer vision techniques.
There are numerous challenges in this problem, including: changing grass colors and illumination, moving camera, occlusions, small soccer ball, interfering field marks in the color of the ball, ball moving at different directions and speed, ball shape distortion at frames due to high speed, ball changing size with respect to distance from the camera and more.

Related work:

1. A computer vision based web application for tracking soccer players
2. Stanford University paper for computing soccer stats with computer vision.
3. Technical University of Munich paper for Detection of Individual Ball Possession in Soccer.

Technical Description & Algorithm



Methods used and learned in class

Object detection & recognition:

- Color filtering is used to extract foreground objects
- Tried extracting background color and detect players jerseys using histograms (wasn't good enough so didn't use it at the end)
- Morphological operations such as dilation, erosion & connected components are used to erase unnecessary field lines and reduce noise.
- Shape analysis using contour identification, bounding box and bounding circle for all objects in the game
- Pixel counting based on colors to better team detection
- Used K-means to extract colors more accurately

Object Tracking (ball tracking):

- Region based & Mean-shift methods using adaptive search tracking window and pre knowledge about shape, size and intensity of the ball
- Tried also Kalman Filter to predict ball location when no measurement is available. for example - when there are occlusions

Data used

- Used three videos including short parts of a soccer game between Barcelona & Arsenal.
- The videos are taken from the standard camera which fans use to watch soccer on TV.
- These videos included different camera motion speed, as well as different locations of the field, changing distances of the ball relative to the camera, changing ball possessions, and different ball motions.

Summary of experimental results

For measuring the ground truth we observed on each frame in each video and divide our observations into the next confusion matrix:

TP - Arsenal possesses the ball and we computed that Arsenal possesses the ball	FP - Barcelona possesses the ball and we computed that Arsenal possesses the ball
FN - Arsenal possesses the ball and we computed that Barcelona possesses the ball	TN - Barcelona possesses the ball and we computed that Barcelona possesses the ball

Results:

Video Name	Computed ball possessions by today method (number of passes*)	TP	FP	Computed ball possessions (frames measurement**)	Ground truth - True ball Possessions (frames measurement**)	Precision	Recall
		FN	TN				
	%	Number of frames		%	%	%	%
Vid1 link	Ars - 0% Bar - 100%	74	97	Ars - 61% Bar - 39%	Ars - 40% Bar - 60%	66%	42%
		36	72				
Vid2 link	Ars - 100% Bar - 0%	115	0	Ars - 42% Bar - 58%	Ars - 100% Bar - 0%	100%	42%
		157	0				
Vid3 link	Ars - 15% Bar - 85%	215	107	Ars - 51% Bar - 49%	Ars - 47% Bar - 53%	67%	70%
		94	242				

* Number of passes - sum of passes for each team divided by the game total passes

**Frames measuring - amount of time (frames) each team possessed the ball

Discussion of the results

Overall, we managed to detect the players of each team very well. Ball tracking was a challenging task, and we found that combining various techniques helped get better results, which are not perfect and could be further optimized.

In addition, compute ball possessions from one single camera isn't accurate enough due to occlusions of the ball which sometimes makes false detection of the team possessing the ball. In general, our program should be able to get any soccer video game, with teams' outfit color ranges and produce a video with detected players, teams, ball, and ongoing ball possession.

Player detection:

- Very accurate results using shape and color classification
- Dealing with occlusions of 2 players from different teams
- Robustness to noise, illuminations, distance from camera
- Similar outfits between the teams may lead to false detection
- More than 2 players counted as one contour - Since those cases are rare and doesn't have much importance in our program, we didn't try to solve it

K-means for Object detection:

- Improved results by a few percentage
- Since this algorithm add a lot of complexity to our process we decided not to use it

Ball tracking with region base & Mean-shift methods:

- Deep analysis of the ball features enable nice results
- Adaptive tracking window for cases the ball is moving too fast for small searching window
- Morphological operations and connected components helped avoiding false ball detections, like white signs on the field.
- Shape analysis helped avoid false detection, however we learned that fast ball movement can be seen with distorted shapes on certain frames.

- Bad robustness to long occlusions of the ball
- May be caught tracking areas similar to the shape and the color of the ball (like the center circle of the field)

Calculate ball possessions:

- Worked well when there are few frames which the ball is hidden behind a player
- Worked well when measurement/prediction truly detect the ball
- Sometimes make better calculations from the method is used today that count number of passes
- When occlusion happens it sometimes falsely add possession the wrong team - can be solve by adding another camera from a different location
- When measurement/prediction falsely detect the ball it sometimes brings to wrong possession calculation
- It's a challenge to compute crowded places when the ball quickly passes from one team to another (those cases are also complicated by the method is used today)

We measured videos of a few seconds long. For more confidence conclusions we need to check our algorithm on longer videos

Future work

Player detection:

- Instead of giving the color range of the grass and players, they can be extracted automatically using color and gradients histograms to better identifying the players of each team (update histograms every k frames)
- Classify the referees, the goal-keepers, and other objects around the field to avoid false detection
- Deal better with occlusion by divide the region to several patches, calculate the similarity for each patch, and decide where is the best objects locations (can be solved also with KNN)
- Learn the shape of the field on all the white lines for better dealing with camera movement, locations, and background extraction

Ball Tracking:

- Machine learning methods which learn the ball shape, color, size, and motion for better tracking
- Use several methods in parallel that also produce confidence level, and perform majority voting and weighted average on actual ball location, taking confidence level into account
- Use Kalman Filter to produce better estimations of the ball location
- Avoiding areas on the field which are similar to the ball
- Use optical flow for better analysis of the ball movement direction and velocity.

- Work on other videos with cameras of different angles on the field, and with different times of the day for optimizing the results
- Better adaptive search window which contain more window sizes and shifting between them more efficiently

Calculate ball possessions:

- Add another camera from a different location for better dealing with occlusions
- Test our algorithm on longer videos and detect false measurements