SportsVideo: A Multimedia Dataset for Sports Event and Position Detection in Table Tennis and Swimming

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Abstract

Positions and actions detection/classification are one of the main challenges in visual content analysis and mining. Sports video offer such challenges due to the variety of scenes and actions they contain. Sports also provide a wide range of analysis, related to athletes' performances and tactics. We propose a series of 6 sports-related tasks, divided each into 2 subtasks for two sports, table tennis and swimming. Those tasks are a follow-up from the Sport Task and SwimTrack tasks from the 2022 MediaEval Benchmark.

1. Introduction

We present SportsVideo, a series of six sports-related multimedia tasks, divided in subtasks for table tennis and swimming. The dataset is a merge of the Sport Task (Table Tennis) [1] with SwimTrack [2] (Swimming) task from the Medieval 2022 edition [3] into a single benchmark dataset. The main motivation is to provide a more complete and challenging benchmark for video analysis with complex scenes and actions. The first four tasks are related to image and video analysis, the fifth to sound analysis and the last one to textual information extraction.

By combining two different sports –table tennis and swimming– we aim to encourage an approach that generalizes beyond a single sport type since the two sports are very different in terms of the type of video, the type of events and the type of analysis required. Table tennis is a fast-paced sport with a lot of actions and a narrow field of view. Swimming is a slower sport with a large field of view and a lot of occlusions. We expect participants to develop approaches that can generalize to both, but also to other sports. Those tasks have been identified and designed to be as independent as possible so that participants can choose to participate in one or more tasks. If combined, they can provide a more complete analysis of sports videos for both performance and tactical analysis. Participants are encouraged to release their code publicly with their submission. This year, similarly to the Sport Task 2022 edition [4], a baseline for both subtasks 2.1 and 3.1 is shared publicly[1] [5]. Background on sports is provided in the following two PhD thesis in swimming [6] and in table tennis [7].

MediaEval'23: Multimedia Evaluation Workshop, February 1–2, 2024, Amsterdam, The Netherlands and Online
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[1]https://github.com/ccp-eva/SportTaskME23

2. Tasks Description

Task 1 - positions detection

The main information in sports is related to positions of players in videos featuring different numbers of lanes in a swimming pool and sides around a table tennis (seen from various angles). Participants need to provide bounding boxes for identified players, and their results are evaluated using Average Precision (AP) at an IoU ratio of 0.25, counting true positives and negatives across the dataset.
Subtask 1.1 (table tennis) – To detect 2 or 4 players (depending if single or double) and track them during the video especially during double games where players have a lot of overlaps, from videos recorded from various angles (e.g., side, corder).
Subtask 1.2 (swimming) – To detect up to 8 swimmers in the pool from static videos (recorded from the side of the pool). A baseline is provided in [8].

Task 2 - event detection

Key information in sports video is related to events, in particular strokes, which are related to a particular time and typology. Participants are however only required to identify the timestamp of the event, the classification is achieved with the next subtask.
Subtask 2.1 (table tennis) – To detect when a player is performing a stroke (i.e. a ball hit with the racket) using close-up videos. The goal is to detect the exact frame when the ball is hit by the racket. Videos are provided with ball position. Evaluation is based on the F1-score, which measures the harmonic mean of precision and recall.
Subtask 2.2 (swimming) – To detect each time a swimmer is achieving a repeated motion for each swimming style (for Freestyle, Backstroke, and Butterfly stroke once the swimmer's right hand enters the water; for Breaststroke once the head is at its highest point). Swimmers' strokes are identified after the underwater phase and until the swimmer finishes the race, excluding underwater phases for races longer than 50m. Video clips of cropped swimmers only are provided, and evaluation is based on Off-By-One Accuracy, which measures the proportion of correctly estimated stroke counts within a tolerated error of one stroke in the dataset. A baseline is provided in [9].

Task 3 - event classification

The goal of this task is to classify the type of stroke performed by a player in table tennis and swimming. Participants need to categorize a collection of shortened table tennis stroke videos, each containing either a single stroke or no stroke. There are 20 potential stroke categories and an extra category for non-strokes. Two sets with annotations are given: a training set with 807 videos and a validation set with 230 videos. The challenge is to classify a non-annotated test set comprising 118 videos, with the assurance that the trimmed videos in each set are derived from the same untrimmed videos but captured at different time instances without temporal overlap.
Subtask 3.1 (table tennis) – To classify different strokes in table tennis from trimmed videos in which only one stroke is present. There are 3 different categories of strokes, services, forehand and backhand. For services we have 6 different classes. For forehand and backhand we have 5 classes. 16 classes and one non-stroke class are provided, for a total of 1156 videos.
Subtask 3.2 (swimming) – To classify different swimming styles (Freestyle, Backstroke, Breaststroke, Butterfly). A total of 96 labeled images are provided.

Task 4 - field/table perspective projection

Sports videos in general, and in particular the ones provided for the SportsVideo task, are usually recorded from the side. This task asks participants to find the homography transformation for each frame in the dataset. It consists in the projection that maps points of the swimming pools or table tennis space, to corresponding points in the video space. The precision of this projection is evaluated using Intersection over Union (IoU), with two metrics: IoU for the visible pool/table parts and IoU for the entire pool/table, including parts outside the camera's field of view.

Subtask 4.1 (table tennis) – To detect the table position for a given video frame of a whole table tennis. The dataset contains 54 annotated images with homography transformation from TV broadcasts of table tennis matches.

Subtask 4.2 (swimming) – To detect pool position for a given video frame. The dataset is provided with 500 annotated images with homography transformation from [10].

Task 5 - sound detection

Sports are highly multi-modal events. Sound is an important modality that can be used to detect events. They can either be used as official cues (e.g., buzzer sound in swimming) or as additional cues (e.g., ball bounce in table tennis). In this task, participants are asked to detect sound events in table tennis and swimming videos. In table tennis, the ball bounces on the table for every stroke.

Subtask 5.1 (table tennis) – Ball hits indicate the pace of the game. The goal is to detect the exact frame when the ball bounces on the table. Videos are provided with the ball annotated and evaluation is based on the F1-score.

Subtask 5.2 (swimming) – A buzzer sound (preceded by an "on your mark") signals the start. Participants are asked to find the time of this sound within audio files extracted from live videos. These files may or may not include the buzzer sound, which can occur at various moments during the recording. This task is challenging because the sound might be recorded from a different position and could be accompanied by a significant background noise.

Task 6 - score and results extraction

In most sports, the outcome is presented on a scoreboard, featuring race time for each swimmer (and possibly extra data like reaction time) or the current score of the game. These scoreboards are typically either physical LCD screens on the wall or close to the referee. Digital versions of scoreboards are also displayed on TV broadcasts as overlays.

Subtask 6.1 (table tennis) – The goal is to extract the current score of the match. In table tennis, the score can be embedded in the broadcast video or it can be shown by referees with scoreboards. When the score is embedded in the video stream, names of players are also displayed.

Subtask 6.2 (swimming) – The task here involves extracting swimmers' names, lane numbers, and race results (times) from screenshots of these scoreboards. The images and scoreboard coordinates will be provided, with the localization aspect already addressed. During swimmer competitions, after each race, results are displayed on digital boards. The goal is to recognise characters of these boards to obtain the results of races.

Conclusion and Perspectives

In the future, we plan to enhance the video database by incorporating additional table tennis and swimming recordings, along with game characteristics (i.e., more camera angles, extended video footage, interactive competitions, and parasports). Additionally, we aim to introduce a grand challenge task that requires participants to reconstruct entire games or races, involving the solution and assembly of all subtasks.

3. Acknowledgement

We thank the people involved in the previous versions of this challenge. This project was partially funded by the ANR NePTUNE, grant number ANR-19-STHP-0004 and the FFTT/ECL/LIRIS partnership convention.

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