GPS Driven Camera Selection in Cyclocross Races for Automatic Rider Story Generation

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Abstract: Cyclocross races are a very popular winter sport in Belgium and the Netherlands. In this paper we present a methodology to calculate the proximity of riders to a number of cameras that are located on a cyclocross course in order to automatically select the correct camera for each rider. The methodology is based on two main input sources. The first input is the course with cameras positioned along it. As the course and camera information is usually available as pdf and isn't directly processable by computer programs, we propose the conversion GeoJSON. The second requirement for our methodology is accurate location tracking of the athletes on the course with the help of wearable GPS trackers. We present an experimental camera proximity algorithm that uses both input sources and finds for every rider at any given moment in the race the closest camera or vice versa. The output of this methodology results in automatic identification of the filmed riders by a given camera at a given moment in the race and might benefit post-processing of the camera video streams for further computer vision-based analysis of the streams, for example, to pre-filter the camera streams or to generate rider and team stories.

1 INTRODUCTION

Over the past few years, cyclocross became more and more global as the UCI World Cup series is organized across the universe, with its epicentre located in Belgium. Races are broadcasted on Belgian and Dutch national television and the action is captured by an array of approximately 20 cameras. The optimal camera stream for a given moment in the race is usually selected by the broadcast director who is monitoring the race footage in the camera truck at the race location. When the race gets very eventful and a lot of action happens simultaneously this can be a rather hectic job. Furthermore, it is not unimaginable that the directors in charge have some subjectivity or their preferences for certain riders or sectors. In the current workflow, a lot of video footage is lost, as only the main broadcast is usually persisted at their servers. As it will be illustrated in this paper and in further research, this is a missed opportunity because having the raw footage at each moment in the race might be valuable to generate additional race insights.

Data-driven race reporting might offer a solution for the previously mentioned shortcomings. The evolution of wearable technology and the implementation of new wireless standards allow race organisers to track every rider on the cyclocross course in real-time. Studies of Hess et al. and Merry et al. show that nowadays fairly accurate GPS tracking is even possible with most of the available smartphones. However, for demanding events such as cyclocross and long road races, a dedicated GPS tracker is used more often. The Quarq Qollector is an example of such a device that tracks GPS location and combines it with sensor data such as heart rate, power and cadence. The sensor is usually mounted on the riders' bikes or at the back of their skinsuit and is transmitting its data in real-time to the Quarq servers using 3G cellular data connectivity. Based on the rider location we can search the camera on the course that is best used to capture the riders. Cyclocross courses are challenging for riders, but also for the film crew to bring the race to the television viewer. The design of a cyclocross track can be considered as "a fine art" as courses are usually built

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by a handful of specialists and often ex-professional riders such as Adrie van der Poel, Richard Groenendael and Erwin Vervecken. Planning, building and finalizing the perfect track takes weeks to provide riders with a challenging, but safe course. Obstacles such as barriers, sandpits and off-camber sectors make cyclocross interesting to watch both at location and on the television. The broadcast director visits the location a couple of days in advance and accurately plans the camera setup at race-day. Cameras, identified by their index number, are placed on a topological map of the course (see Figure 1 for an example of such a course plan).

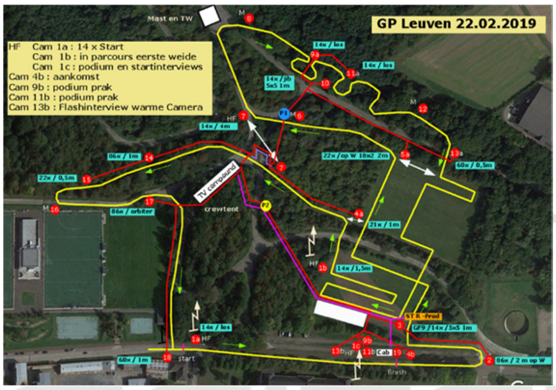


Figure 1: Example pdf document of the race broadcasters plan of the Leuven cyclocross track. Plan contains the course (yellow line). Cameras are annotated as red circles. It is a very detailed plan of the course but is not directly processable by a computer program.

The combination of the multiple camera streams, detailed riders' locations and carefully planned and documented course and camera location make the cyclocross broadcasting a very interesting use-case for automation. As mentioned, camera selection and race monitoring can be very hectic at times. In literature several implementations that predict the best camera at given circumstances based solely on the camera streams exist. Shen and Fels proposed a methodology that produced a Quality of View (QOV) measurement for classifying the quality of each shot in a multi-camera surveillance system. In a sports related context, Chen et al. implemented a methodology to automatically select the correct video camera stream based on Internet videos in soccer games. However, in this paper we present a mechanism that tracks the riders' location based on either GPS files or real time data and returns the closest camera to a given rider. Video editors and directors could benefit from this mechanism as streams can be pre-filtered based on the vicinity of riders. Finally, it can also be used to generate a summary of a rider/team across all cameras.

2 METHODOLOGY

In this section we introduce the steps of the methodology to match a rider based on its GPS location to the closest camera.

2.1 Course Digitalisation

The first step to a GPS assisted camera proximity algorithm is the digitalisation and annotation of the racecourse and cameras positioned along that course. Currently this is a partly manual (offline) process in which a portable document format (pdf) and a gps exchange format (gpx) file are used as input. The gpx file can be either provided by a rider who did practise on the course or it can be drawn with tools such as Komoot, RideWithGPS or Garmin Connect. This gpx file of the course is converted with a Python script to a GeoJSON linestring object. GeoJSON is a very useful standard to store, represent and programmatically access geographic data. The linestring of the course consists of interconnected points (latitude/longitude pairs) of the track (red line, Figure 2).

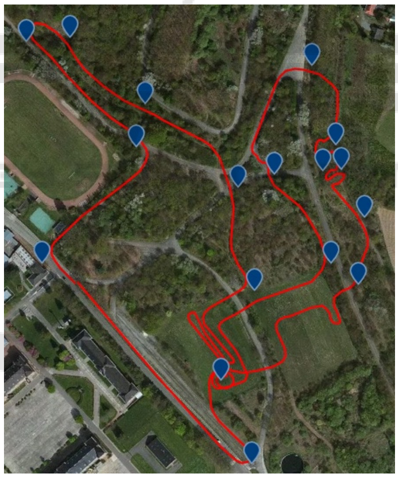


Figure 2: Digitalized version of the cyclocross course of the Rectavit Series Leuven (2020) based on Figure 1. Red line is the GeoJSON course linestring. The blue markers are GeoJSON point features and are representing the cameras and their respective identifiers (camera id).

The locations of the cameras are registered by the broadcasters in a pdf containing both the course and the locations of the various cameras across the track. Every camera on the schematic has an identifier (e.g. Camera 7a), but the logic behind the numbering isn't related to its exact location on the track. To make this camera locations programming interface friendly, we manually added the locations to the GeoJSON track file of the previous step. The installed cameras on the course are stored as GeoJSON point features with the identifier of the camera as its properties (see Code 1 for the json code representing the camera location of camera 2). The camera digitalisation is a rather manual procedure, but tools such as GeoJSON.io are making this rather straightforward. Future work will also further focus on the development of a tagging tool that can automatically generate the GeoJSON data.

```
{
        "type": "Feature",
        "properties": {
              "type": "camera",
              "camera_id": 2,
    },
    "geometry": {
              "type": "Point",
              "coordinates": [
                    4.710833430290222,
                    50.85269722820937
              ]
        }
}
```

Code 1: GeoJSON code representing the "camera 2" coordinates on the course as a point geometry. The feature has its type and camera_id stored as the properties.

2.2 Rider Location Processing

Once we have a structured representation of the track and the cameras placed around it, we can start looking for riders on it. As mentioned in the introduction, several methods do exist to accurately track and trace riders on the cyclocross course. We divided rider tracking in two separate approaches. In the first approach, GPS eXchange (gpx) files were used to get time stamped locations of the riders, who recorded their races with their own GPS head units or watches. These kinds of files are usually uploaded to online web applications such as Strava, Trainingpeaks or Today's plan for further analysis. Although this is not offering us real time locations of the riders, it still provides great information for our camera and rider matching algorithm for post-race video analysis and summarization. Another benefit of using this approach is that there is no need to interface with external Application Programming interfaces (APIs) and real-time storage and management isn't an issue.

The second approach to get the riders' locations is by using one of the many connected GPS trackers (eg. SPOT or Quarq Qollector). These GPS trackers are usually worn on the riders' bodies or fixed to their bikes. Most of the trackers are accessible by APIs.

A Python program was written to interface, read and interpret the data from the Quarq qollector API. Each Quarq Qollector device has a tracking id (tid). With the API we were able to periodically (every second) retrieve all the sensor and location data that was recorded by the Quarq Qollector for a list of participating tracking ids.

Both approaches result in the location of the tracked riders for any given moment during the race. An abstraction layer was written to quickly get a location for a specific rider at a given timestamp, independent from the underlying rider tracking technology.

Riders are often tracked with an identifier. For further computer vision-based analysis on the camera streams the riders' names and other relevant information about them should be linked with the tracking identifier. The linking process should be generic and future-proof. The connection of the riders' identities with the tracking devices should introduce the least manual effort as possible. In cyclocross, new teams appear, and old ones disappear rather quickly. Riders' contracts can range anything from one year to three years, so riders changing teams is very common. The open WikiData knowledge base is the perfect data provider for this information. Most of the riders playing a key role in the race are well documented in WikiData. Their WikiData entries (also called entities in WikiData) are often containing lots of meta-information, such as their height, weight, team history, birthday and many more. WikiData is maintained by a rather active community of contributors around the world. Everybody can propose changes to a WikiData page. For instance, during 2020, the page of famous cyclocross rider Wout Van Aert has been already changed/improved more than five times. This example makes it safe to say that important changes such as team changes or big victories will most likely be updated quite quickly. Finally, the WikiData knowledge base can also be easily exported as a Javascript Object Notation (JSON) document or queried using the SPARQL query language. An example query to the WikiData SPARQL endpoint is shown in Figure 3. As illustrated and if available a royalty free "profile" picture is also retrieved.

It is important that rider ids are linked to the WikiData entity id (QID) for further analysis of the video streams. Currently the link between the location tracking ID and the tracked rider's WikiData QID was made manually. For each tracked rider we make a list that projects each tracking ID number on the athlete's WikiData QID that produces the tracking data. This process would become much easier if riders would have a fixed location tracking ID as well (i.e. if they were using the same trackers every race).

```
# Cyclocross riders with their nationality and picture
SELECT DISTINCT ?riderLabel ?nationality ?pic WHERE {
  ?rider wdt:P27 ?nationality.        #retrieve nationality
  { ?rider wdt:P106 wd:Q15117415. }   # rider has occupation
                                      #  cyclocross-cyclist
  UNION          # or
  {
    ?rider wdt:P279 wd:Q2309784;     # rider is instance
                                     #  of a sport cyclist
      wdt:P413 wd:Q335638.           # and has cyclocross
                                     #  as a specialty
  }
  OPTIONAL { ?rider wdt:P18 ?pic. }   # retrieve image
                                       #   (if available)
  SERVICE wikibase:label { bd:serviceParam wikibase:language "en". }
}
```

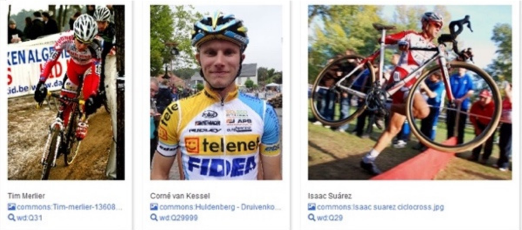


Figure 3: Example SPAQRL query that retrieves all cyclocross riders from the WikiData knowledge base with their WikiMedia image. Result can be stored as JSON or XML. This produces useful rider meta-information for further computer vision-based video stream analysis.

2.3 Camera Rider Matching Algorithm

Now that racetrack, camera locations and rider locations are available and converted to a computer-understandable format a camera matching algorithm can be introduced.

As a start, a formal definition of the proximity of a rider to a certain camera should be given. The calculation can be tackled in a couple of different ways. A first possibility might be the calculation of the haversine distance between a rider and all of the available cameras. The haversine distance is a formula that is very important for geospatial purposes as it is calculating the distance between two points (using their latitude and longitude coordinates) on a sphere (i.e. the earth) (Ingole and Nichat, 2013).

In some cases, haversine distance can be enough, but sometimes the track layout of a cyclocross race might not be ideal for this calculation method. Tracks usually consist of lots of tight turns on a compact area. Figure 4 illustrates this principle. The yellow circled camera is the one that is detected as closest to the rider (represented by the red X). This might result in a good shot of the rider, based on the orientation and direct visibility of that specific camera at this location.

Another possibility is to project both the cameras and the riders on the course's linestring (Westra). The proximity of a camera is now determined by the distance along the course from the rider to the projection of the camera (see Figure 5). The projection is achieved by finding the index of the point on the course with minimum (haversine) distance to the camera's location. If n is the number of cameras and l the number of course points this approach has a time complexity of $O(l \cdot n)$. As mentioned, camera and course data are available prior to the race so this step can be pre-processed for faster real-time querying.

A final optimization that can be done is the pre-indexing of the course points based on the closest cameras (see Figure 6). Finding the closest camera for a given rider is reduced to a search in a precomputed list that is mapping each point on the course to the best/closest camera.

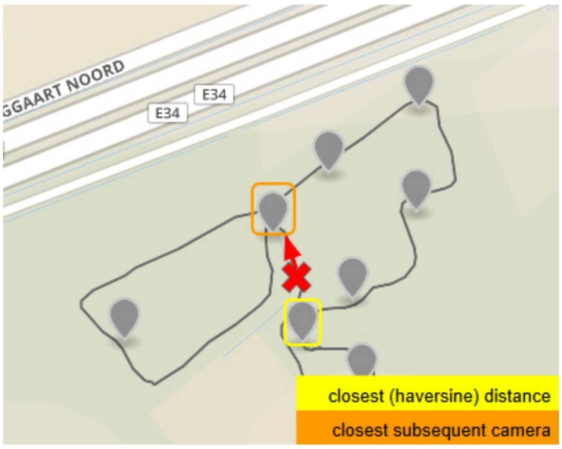


Figure 4: Camera setup on a test course. The red X is the current location of the rider following the course in the direction of the red arrow. Yellow circled marker is the absolute closest camera. Orange circled marker is the next camera the rider will visit on the course.

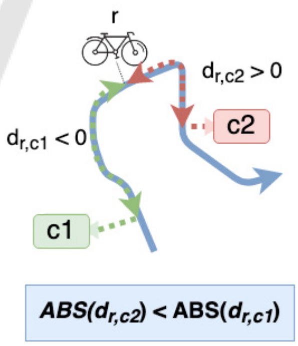


Figure 5: Illustration of closest camera along the course principle. Rider r is "snapped" on the blue course line following the direction of the arrow. Cameras c1 and c2 are also projected on the course linestring. Distance d is the distance from rider r to a camera c with a given index, following the course path. Negative distances are cameras behind the rider, positive distances are cameras the rider is approaching. Closest camera is the camera with the smallest absolute distance.

It is worth mentioning that labelling which camera is serving which point on the courses can also be done manually by the responsible video director prior to the race (resulting output is similar to the output of the pre-indexing approach, Figure 6) . Although this process is a manual effort (that can be facilitated by a software tool), it will in some situations be more accurate, e.g., when dense forests, elevation differences or audiences are blocking the direct view of the closest camera.

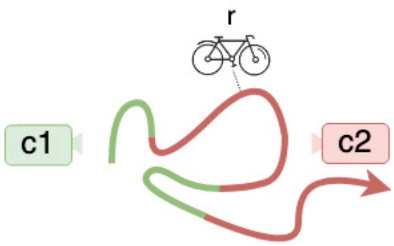


Figure 6: Alternative straightforward approach. Only riders are projected on the course. Each point on the course is labelled with the camera that is serving that location on the track. This can be done by the race directors prior to the race or can be the result of the camera on course projection technique. Getting the closest camera is now a case of looking at the camera index of the point of the rider on the course. Distance to the camera can also be pre-processed for each point on the course using either the haversine or the distance across the course metric.

Now that we know the closest camera for a given rider, we also want to get an idea how far away that camera is. Figure 5 explains the distance ($d_{r,c}$) between a camera *c* and the rider *r*. The distance is not the direct distance between both points but is again the distance along the course's path. A negative distance means that the camera is behind the rider and positioned earlier on the course. A positive distance means that the rider is approaching this camera.

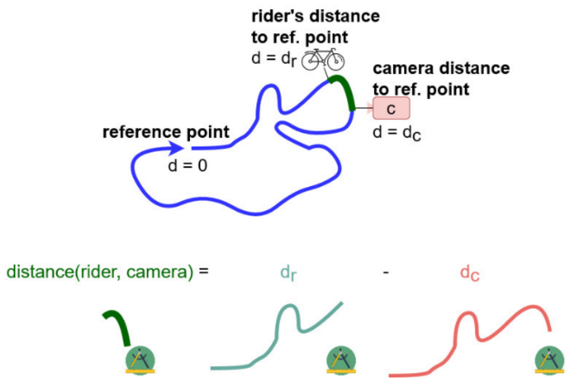


Figure 7: Visual illustration how the referencing approach uses distances w.r.t. a reference point. The distance between two points is the result of the difference between distances from both points to the reference point.

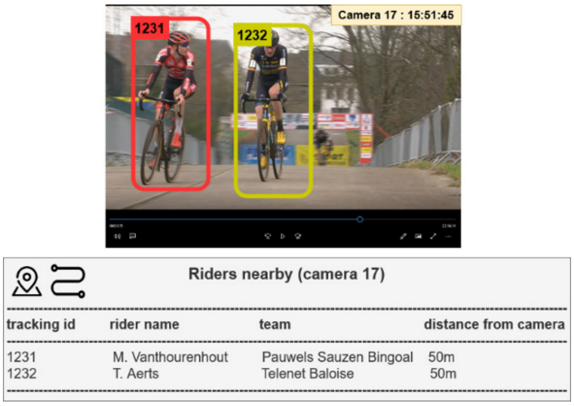
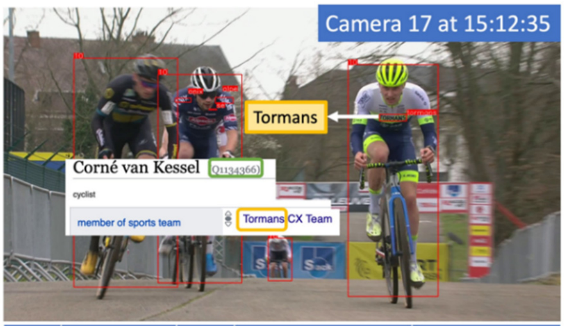


Figure 8: Example output of the camera matching algorithm for a cyclocross race of the 2019-2020 season. Manual verification in the video stream shows that riders 1231 and 1232 are indeed visible by the camera. This shows the feasibility of tracking a rider during the race across the available cameras which is facilitating the video searching process.

To further speed up the camera matching algorithm the distances of riders and cameras on the courses were mapped with respect to a fixed point on the course. We choose the start of the course as the reference point (see Figure 7). This allowed pre-indexing all camera projection locations elapsed distances w.r.t. the course starting point. Finding the distance between a rider and a camera with given index is now a case of finding the elapsed distance of the rider (projected on the course line) w.r.t the course reference point, look up of the elapsed distance of the camera's elapsed distance (w.r.t course reference point) and subtracting both distances.

3 RESULTS

With the introduced building blocks, we can now track riders on the course and find their distances to a given camera. This approach facilitates several interesting analyses. A first possibility is the sorting of riders based on their proximity to a certain camera. Figure 8 shows an example of such a search for the cyclocross race of Leuven around minute 50 of the race. Solely based on sensor data and the course and camera metadata we can reduce the number of riders that might have been filmed by a certain camera. As an example, and as shown in Figure 8, the total number of riders nearby was limited to only two of 13 riders. From one side this methodology might give us an idea of how many and who to expect at a given camera at a given moment in the race. This can for example be very interesting to limit the number of



Rank	Distance to camera	Bib	Name	Wikidata QID
1	75m	6	Corné van Kessel	Q1134366
2	139m	7	David van der Poel	Q3019068
3	147m	45	Niels Vandeputte	Q84839468
4	207m	32	Jarno Bellens	Q89982436
5	225m	24	Nicolas Cleppe	Q22328183

Figure 9: Example of how camera proximity algorithm can help computer vision techniques with rider identification.

candidates for automatic rider recognition/annotation. On the other side a certain rider could also be followed across the different cameras which enables the tracking of a specific rider across all cameras during the race. This can be useful for teams or for fans who are only interested in their favourite rider.

Table 1: Benchmark setup with execution times of pre-processing stage and of some scenarios of the Leuven cyclocross case.

Test setup – race moment 22/02/2020 15:05:43	
Hardware	Apple MacBook Pro (2018) Intel Core i5 – 2.3 Ghz – Quad Core 8GB RAM Intel Iris Plus Graphics 655 1536 MB
Total number of cameras	17
Total number of riders	13
Pre-processing	45.5 s
Loading configuration	0.01 s
Distance all riders to all cameras	3.11 s
Distance 1 camera to all riders	0.18 s *
Distance from 1 rider to all cameras	0.23 s *
** time scales linearly when #cameras/riders increase.*	

The last cyclocross races were held before the suggested methodology was developed, we could only test this approach in an offline manner. Nevertheless, it is important that the performance of the implemented workflow is appropriate for real-time querying as well. To verify the feasibility of live camera proximity tracking in cyclocross races, the proximity algorithm was tested in several different race scenarios. Detailed results of the test can be found in Table 1. We used a total of 17 cameras and 13 riders with tracking information in this test. The most expensive operation was the retrieval of proximity of all riders to all cameras, which took roughly 3 seconds. This can be improved with further reasoning and knowledge of the sequence in which the cameras were positioned. For instance, if only one of the 17 cameras detects nearby riders, it doesn't make sense to run the camera proximity algorithm five seconds later on a camera that is on the other side of the course. Moreover, as GPS systems have an accuracy of around 10 meters (Fong et al.) and riders are riding at speeds ranging between 3 and 15 m/s, the execution time of 3 seconds is justifiable.

```
#EXTVLCOPT:start-time=28
#EXTVLCOPT:stop-time=36
camera_1.mp4
#EXTVLCOPT:start-time=500
#EXTVLCOPT:stop-time=550
camera_17.mp4
#EXTVLCOPT:start-time=900
#EXTVLCOPT:stop-time=1100
camera_5.mp4
```

Code 2: Sample .m3u file. An m3u file is a kind of playlist that extracts specific parts from larger video files (in our example the different camera streams) and plays them subsequently.

With this information in mind, we can start collecting video extracts from different camera streams and compile them in either a rider specific summary or extract only the parts from a raw camera stream in which riders were nearby. When the streams are available as individual files (e.g. *camera_1.mp4*, *camera_17.mp4* and *camera_5.mp4* in code extract 2) it is possible to make an m3u playlist which is bundling all the separate clips as one continuous video, without the need to duplicate the data of the original camera streams (Garcia et al.). Code extract 2 shows the content of an m3u file, selecting 3 video extracts from three different camera stream files.

4 CONCLUSIONS AND FUTURE WORK

The proposed mechanism is not only useful for race broadcast directors, but the filtered streams can also be further processed by video processing algorithms to annotate, index and document the race footage. The camera proximity algorithm can serve as a first filter for the video footage before it is processed by the video processing tools which are also currently being developed within our cyclocross video research project. Techniques such as text recognition, face recognition and pose estimation are used to further annotate the filtered video extracts from the camera streams.

The camera proximity algorithm can also further assist the computer vision modules (Xue et al.). Currently the main components of our computer vision pipeline are a Detectron2 pose estimator to locate the riders and a Keras-OCR (Python library that combines a CRAFT text detector and CRNN text recognition to read jersey numbers and sponsors, Nag et al. and Baek et al.) and text recognition module. For instance, as the example in Figure 9 illustrates, our text recognition detects "*Tormans*" and the output of the camera proximity algorithm (see table in Figure 9) outputs that only one rider of that team is in the neighborhood of the camera in question (i.e. *camera 17*). Combined with the help of the WikiData information available about the riders and their teams, we can easily find out the rider's identity (i.e. *Corné van Kessel*).

Moreover, the use of WikiData information of riders has also been found to be beneficial as it offers a semi-automated way to get up-to-date data about riders. In the future we plan to even further extend this WikiData approach. Participants of a cyclocross race are usually available as a PDF document roughly an hour before the race. We are currently writing a Python library to process these formatted PDF documents and extract riders and their bib numbers. A similar approach can be used on the PDF of the race results. The parsed information of both PDF documents can then be committed to the WikiData page of the cyclocross race. New WikiData entities are automatically created if the race or rider isn't on WikiData yet. Ultimately, this extra information could be very helpful to link the output of the camera proximity algorithm with insights gathered from the computer vision techniques applied on the camera streams. For instance, in Figure 10, the WikiData race participant information helps the computer vision pipeline to identify the rider based on the shoulder number on the rider's left arm.

Figure 10: Example of optical character recognition (OCR) on camera 17 output stream. With the combination of the detected shoulder number and the participant list added to the race's WikiData page the rider was correctly recognized. In combination with the camera proximity algorithm this can produce an accurate rider detector and tracker.

As mentioned, another aspect we're currently focussing on is the creation of an intuitive camera coverage labelling tool for the race directors. Such a tool should allow them to easily label the locations of the cameras on the racecourse using a web application on a wearable device. The tool could do the conversion process to the GeoJSON standard automatically, which would be a huge step towards a fully automated camera proximity algorithm.

As a final note, the proposed methodology of linking participant location data with camera and course/playfield information can also be repurposed in other sports such as cross country skiing (Swarén et al.) or motorsports. With some adaptations the proposed methodology can also be used in team sports such as hockey, rugby or soccer. However, these type of team sports might benefit from a more accurate location tracking system such as Ultra Wide Band (UWB) or Radio-Frequency Identification (RFID) (Gudmundsson and Horton) position tracking as GPS accuracy errors and the relatively small dimensions of the playgrounds might give false camera proximity results (Castillo et al.).

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