

## Implementing the tracking of 1500 m runners using Open CV

YONGCHANG YANG<sup>1</sup>, XINWEI LEE<sup>2</sup>, YASUSHI ENOMOTO<sup>3</sup>

<sup>1</sup>Doctoral Program in Physical Education, Health and Sport Sciences, University of Tsukuba, JAPAN

<sup>2</sup>Graduate School of Systems and Information Engineering, University of Tsukuba, JAPAN

<sup>3</sup>Faculty of Health and Sport Sciences, University of Tsukuba, JAPAN

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### Abstract:

**Purpose:** This study uses OpenCV to recognise and track runners in a 1500 m race video, output their actual coordinates and calculate their actual running distance and speed. By tracking middle-distance runners, their running performance can be analysed. The traditional method of video recording and analysis for a 1500 m race can be replaced by artificial intelligence techniques. **Method:** This study uses a 4K high-definition (3840 × 2160 pixel resolution) camera for fixed shooting at 30 fps with a wide-angle lens and MP4 video recording format. AutoCAD was used to draw and measure the actual coordinates of the playground, and OpenCV enabled the image recognition and tracking of runners in the 1500 m competition video, output their image coordinates, calibrate the image coordinates with the actual coordinates and output their coordinate trajectory over the 1500 m distance, thereby calculating their speed in 100 m intervals. **Results:** Using the actual coordinates, one of the runners actual running distances was calculated as follows: the 0–300 m section was 298.9 m, the 300–700 m section was 402 m, the 700–1100 m section was 404.6 m and the 1100–1500 m section was 404.7 m. In the 1500-m race, the runner ran approximately 10 m more than the official distance. In terms of speed, we compared the effectiveness of object tracking and manual video analysis in calculating speeds per 100 m. There was no statistically significant difference between the two data sets ( $P = 0.23$ ), and the difference was less than 0.5 s. **Conclusion:** Based on OpenCV, the identification and tracking of runners in the competition video can basically be realised, and the actual distance runners cover during the competition can be calculated. However, there are still difficulties in the object-tracking process. This study is the first to use object tracking in middle-distance running over 1500 m. Middle-distance races are more complex than sprint races, which undoubtedly present substantial object-tracking challenges. However, this new attempt will undoubtedly provide new ideas and references for the analysis of middle-distance races in the future.

**Keywords:** 1500 m, OpenCV, Object tracking, Middle-distance running

### Introduction

With various developments in science and technology, research on interdisciplinary integration is expanding. Single-subject research has failed to meet the needs of modern society. Among these, the invention of computers has promoted the development of sports modernisation, improved the accuracy of different sports events, corrected certain technical movements of athletes, and realised some technical evaluations that are difficult to judge with the naked eye (Kuruppu et al., 2013). When analysing sports competitions, video analysis is frequently an important methodology for coaches, athletes, and researchers. The development of modern camera technology has greatly improved video quality, and it has become possible to obtain various types of videos through various channels. For a long time, the 1500-m race has been analysed manually using video. The analysis interval is used to analyse the speed of runners every 100 m (Mtsuo et al., 1992; Enomoto et al., 2006; Yang & Enomoto, 2022). However, this analysis method obviously cannot satisfy the overall race analysis for runners, and the race analysis efficiency is low. Since the manual analysis of competition videos is laborious and time-consuming, its automatic analysis has been widely adopted. This mainly integrates image processing, machine learning, and artificial intelligence, among other fields. Therefore, automatic video analysis has been widely used in technical analysis, video monitoring, athlete tracking, and similar pursuits (Sheng et al., 2020; Wang et al., 2019).

The technical level of sports training has evolved slowly over the past few decades; it mainly adopts traditional subjective and empirical teaching approaches. The coach observes their athletes' technical movements with the naked eye and through experience. Meanwhile, athletes are equipped with various sensors to detect and track quickly and accurately to obtain useful information. However, this traditional method places extra burdens on athletes and seriously affects their competitiveness (Ghasemzade et al, 2010; Sheng et al., 2020). At the same time, laboratory measurements are of limited use because exercise machines do not perfectly simulate natural activities and it is difficult to replicate outdoor environmental conditions. Laboratory tests on athletes are typically performed occasionally, further restricting the amount of useful information that can be obtained

(Wixted et al.,2010). With the development of computer vision technology, image-based methods for non-contact human motion analysis have emerged (Su et al., 2022). In recent years, the development of object detection and tracking technology has given athlete tracking and recognition in video a great deal of attention. Practise and research show that the introduction of digital video technology in sports training is conducive to improving training efficiency. This includes detecting and tracking the motion parameters of video and analysing behavioural characteristics. The detection and tracking of athletes in videos as a non-contact method has been widely studied and applied in basketball, football, swimming, and volleyball, among other sports (Dearden et al., 2006; Xing et al., 2010; Lu et al., 2013; Lu et al., 2013; Manafifard et al.,2017; Victor et al.,2017;Yuta et al., 2020 ). However, there is little research on the detection and tracking of track and field athletes in videos.

Video-based detection and tracking methods for athletes help analyse the competition process more accurately and quickly. However, there are many difficulties in the process of identification, detection, and tracking. These include follow-up predictions after starting sprinting, the similarity between athletes' contours, complex interactions during races, the large-area occlusions of obstacles, the variety of outdoor environment changes, the camera's performance, and the differences in personal video shooting techniques. These factors pose significant challenges to the implementation of object detection and tracking (Sheng et al., 2020). In addition, human action recognition has been widely used in video surveillance, motion analysis, and medical detection, and studies on human posture estimation and recognition are increasing (Xu et al., 2022). The motion recognition and evaluation system can provide quantitative analysis results of motion integrity and synchronisation, assist practitioners in standardising actions, and improve exercise benefits. Based on the development of object detection and tracking technology, it remains unknown whether it is possible to track middle-distance runners. Therefore, to monitor middle-distance runners, overcoming obstacles such as a track and field that is too large, objects that are too small, and other limitations is of great importance. This research uses high-definition video shooting to collect middle-distance 1500 m race videos as the research object, uses OpenCV to realise the recognition and tracking of runners in a 1500 m race video, outputs their actual coordinates, and calculates their actual running distance and speed. The running performance of middle-distance runners can be analysed through tracking. It can provide some inspiration for the automatic analysis of middle-distance running videos.

## Methods

### *Coordinates of track and field grounds*

The competition analysed was the 2020 Japanese National Championships, organised by the JAAF. To determine the coordinates of the track and field grounds, the track and field area was surveyed and confirmed prior to the competition. In this research, AutoCAD was used to draw the site and measure coordinates. The track and field ground was a standard 400 m with nine tracks. The two semicircles had a radius of 37.9 m, and the rectangle was 80 m long and 75.8 m wide. The outer side of the starting point's nine lanes for the 110 m hurdles was taken as the origin point (0, 0) (Fig. 1). Coordinate processing was prepared for the image-coordinate and actual-coordinate calibrations.

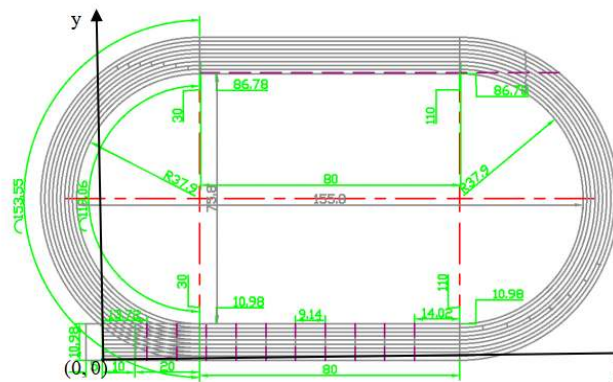


**Fig.1.** Determining the coordinates of the 400 m track and field ground using AutoCAD  
*HD video shooting*

In this study, we collected the finals of the 1500 m race using fixed and panning videos. Two cameras were used simultaneously for video recording. One camera was for panning shooting, during which it tracked and shot the runners along the ground track. The shooting speed was 59.94 fps, the shutter speed was 1/60 s when using a flash gun, and the camera speed was 1/500–1/1000 s until the end of the race. The video had a 1920 × 1080 pixel resolution and was set in MP4 format. The other camera was fixed with a bracket and had an HD 4K (3840 × 2160 pixel) resolution with a shooting speed of 30 fps and a wide-angle lens frame (focal length: 10–18 mm) for taking panoramic shots of the track and field ground (Fig. 2). Before shooting, the F-value, ISO sensitivity, and focal length of the camera were adjusted depending on weather changes and shooting distance.



**Fig.2.** 4K HD panoramic picture of Niigata, Japan stadium  
**Tracking Algorithm**

Object tracking, an important branch of machine learning, is widely used in various fields. OpenCV has eight tracking algorithms, including CSRT, KCF, BOOSTING, MIL, TLD, MEDIANFLOW, GOTURN and MOSSE. Each algorithm has unique characteristics. Correlation single-object tracking (CSRT) is a method for tracking moving objects in video sequences based on correlation filters. The CSRT algorithm has good tracking performance for different targets, motion patterns, and image backgrounds. The main concept behind the CSRT tracker is to use a template to represent the target to be tracked. In each image frame, the CSRT tracker uses correlation filtering to search for regions that match the template and to find the best-matching region as the current target position. The target's template is modified to accommodate any changes to the target. The advantages of the CSRT tracker include: (1) High accuracy: Compared with other single-object tracking algorithms, the CSRT tracker has higher accuracy. (2) Strong robustness: The CSRT tracker is robust to complex situations such as target deformation, rotation, and occlusion. (3) Fast speed: The CSRT tracker has good real-time performance and can operate in high-frame-rate video streams. The CSRT tracker was selected in this study due to its high accuracy and ability to track small targets in HD video. We improved the original algorithm to better track and output image coordinates. Figure 3 shows the tracking effect.

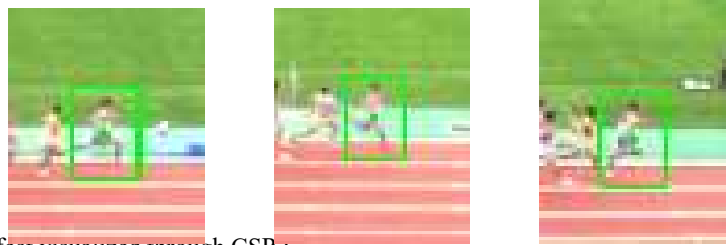


**Fig.3.** Tracking effect visualized through CSRT

### Coordinate transformation

In this study, the position of athletes on the athletic field was determined using projective transformation from a two-dimensional image of the camera's point of view obtained through video recording (Kinoshita & Tomoeda, 2019). The selected coordinate points of the known Fig. 4 and the actual coordinate points of the AutoCAD (see Table 1), and the coefficient  $M$  (Eq. 3) can be obtained through calculation by using perspective transformation (Eqs. 1 and 2), where  $x'$  and  $y'$  are the image coordinates and  $x$  and  $y$  are the actual coordinates. Given the image coordinates after video tracking and the coefficient  $M$ , the coordinates of all movement tracks for the runners can be calculated.

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = M \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad \dots\dots\dots (1)$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad \dots\dots\dots (2)$$

$$M = \begin{bmatrix} -0.08 & -0.14 & 191.57 \\ 0 & 0.13 & -205.75 \\ 0 & 0 & 1 \end{bmatrix} \quad \dots\dots\dots (3)$$

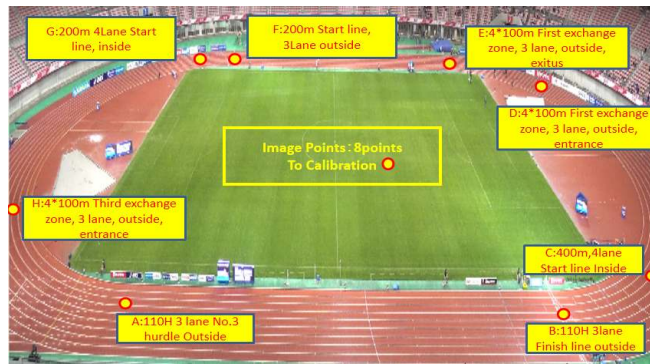


**Fig.4.** Image points for calibration

**Table 1.** Corresponding points between image and actual coordinates

| Points | Actual points |              | Image points |              |
|--------|---------------|--------------|--------------|--------------|
|        | X-coordinate  | Y-coordinate | X-coordinate | Y-coordinate |
| A      | 32            | 7.32         | 712          | 1567         |
| B      | 110           | 7.32         | 3235         | 1582         |
| C      | 131.21        | 13.14        | 3752         | 1502         |
| D      | 139.97        | 77.67        | 3060         | 1053         |
| E      | 112.72        | 90.35        | 2560         | 1005         |
| F      | 30            | 90.44        | 1297         | 994          |
| G      | 19            | 88.95        | 1122         | 998          |
| H      | -4.67         | 25.96        | 19           | 1337         |

## Results

Figure 5 shows the output image coordinates after tracking the captured video with OpenCV. In this study, the video was divided into four parts: one 300 m interval and three 400 m intervals. During the competition, there were billboards and other obstructions on the track and field ground, and tracking breaks occasionally, so we could only continue tracking by overcoming the obstacles. In comparison to short-distance tracking, it is more difficult to accomplish complete tracking at a distance of 1500 m. Figure 5 clearly demonstrates that the image coordinate track is complete except for a few places where obstructions have caused fractures. Second, the large size of the track and field and the very small size of the athletes in the video impede surveillance efforts.

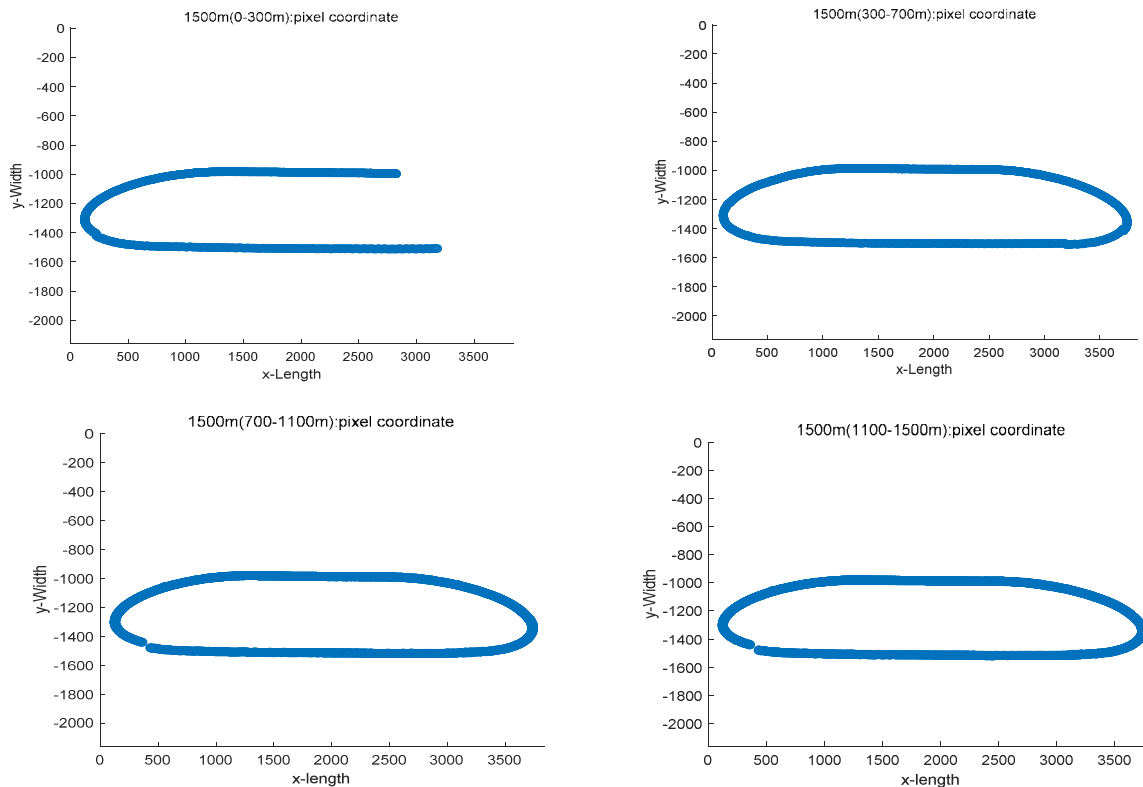


**Fig.5.** Image coordinates of a 1500 m runner after tracking

Figure 6 shows the actual coordinates after correcting and smoothing the tracking output image coordinates. This study uses runner I as the tracking target and output. The blue line is the actual coordinate track after calibration from image coordinates, and the yellow line is the track that has corrected the blue coordinates by 0.8 m. The black circle is the inner edge of the playground. Using the output of the actual coordinates, the actual running distance of runner I was calculated. Although the event is a 1500 m race, through tracking and calculating runner I's position, we can see that they ran 298.9 m in the first 0–300 m, 402.1 m in the 300–700 m section, 404.6 m in the 700–1100 m section, and 404.7 m in the 1100–1500 m section. This is 10.3 m more than the actual 1500 m race distance.

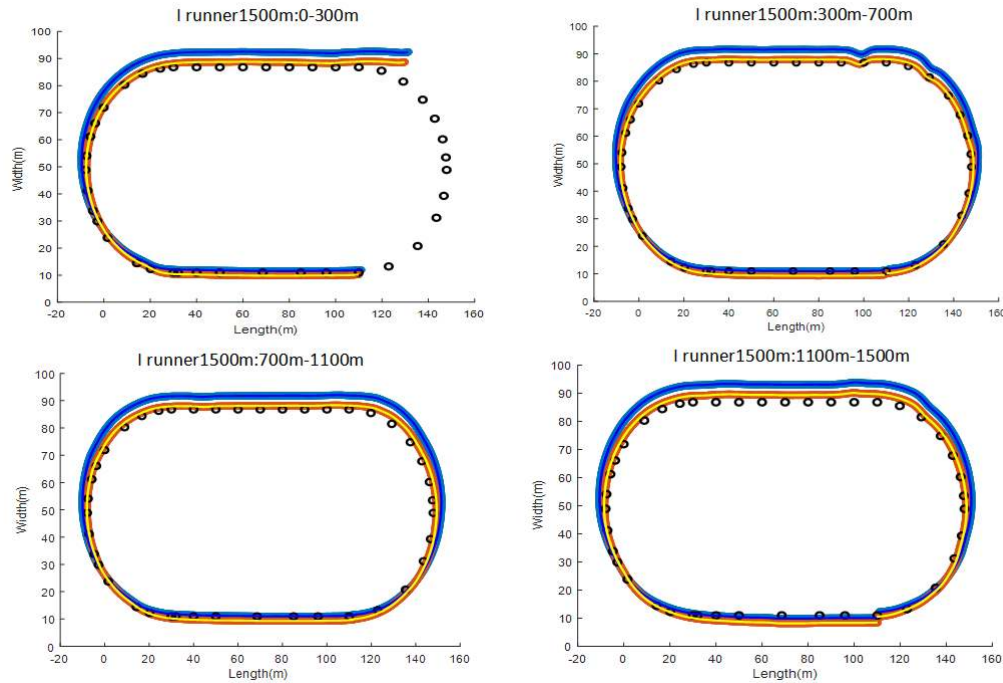


**Fig.6.** The actual coordinates of tracking after calibration from the image coordinates  
(---Original actual coordinates; --- Coordinates corrected by 0.8 m; “○” The inner edge of the playground)

Table 2 compares the effectiveness of target tracking and manual video analysis for calculating speeds per 100 m. To validate the feasibility of our algorithm, we used two different cameras for video recording in the study. One camera was used for tracking shots (shooting speed: 59.94 fps), and traditional manual methods were used for speed analysis of the player's 100 m interval. The other camera was used for fixed shooting (shooting speed: 30 fps), and OpenCV was used for player tracking and speed calculation (see specific methods in the research methods video shooting section). According to Table 2, there was no statistically significant difference between the two data sets ( $P = 0.23$ ), and the difference between the two data sets was less than 0.5 s. Therefore, we can conclude that using OpenCV for target tracking produces speed outputs that are very close to those obtained from traditional manual methods. Thus, OpenCV can be used to identify, track, and calculate the speed of 1500 m runners.

**Table 2.** Comparison of object tracking speed and manual video analysis speed per 100 m

| Distance (m) | Object tracking speed (s) | Manual video analysis speed (s) | D-value (s) |
|--------------|---------------------------|---------------------------------|-------------|
| 0–100        | 7.20                      | 7.25                            | -0.05       |
| 100–200      | 7.05                      | 6.85                            | 0.20        |
| 200–300      | 6.74                      | 6.56                            | 0.18        |
| 300–400      | 6.55                      | 6.77                            | -0.22       |
| 400–500      | 7.02                      | 6.71                            | 0.31        |
| 500–600      | 6.89                      | 6.54                            | 0.35        |
| 600–700      | 6.60                      | 6.49                            | 0.11        |
| 700–800      | 6.43                      | 6.49                            | -0.06       |
| 800–900      | 6.87                      | 6.42                            | 0.45        |
| 900–1000     | 6.57                      | 6.44                            | 0.13        |
| 1000–1100    | 7.00                      | 6.53                            | 0.47        |
| 1100–1200    | 6.62                      | 6.65                            | -0.03       |
| 1200–1300    | 7.85                      | 7.08                            | 0.77        |
| 1300–1400    | 7.80                      | 7.60                            | 0.20        |
| 1400–1500    | 7.71                      | 7.62                            | 0.09        |

## Discussion

The speed at which an object can be tracked and the speed of manual video analysis can vary depending on various factors, such as the complexity of the environment, the type of target being tracked, and the instrumentation being used, among others. However, in general, automated object tracking systems powered by artificial intelligence or machine learning algorithms can track targets at much faster speeds than manual video analysis. This research is the first attempt to track objects during a middle-distance race. We can basically track the 1500 m runner tracking results through OpenCV, and the actual distance the runners travel in the competition is calculated. However, the current tracking system still faces many challenges, such as object occlusion, illumination variation, and prediction of running start, which warrant further study (Sheng et al., 2020). In addition, because the track and field ground is too spacious, the pixel sizes of the people in the video are inadequate. Although we have used a CSRT tracker to track the runner in this competition video, it is difficult to achieve complete tracking due to the competition's numerous influencing factors.

For a long time, the 1500 m race has been analysed manually using video. The analysis interval is used to analyse the speed of runners every 100 m (Mtsuo et al., 1992; Enomoto et al., 2006; Yang & Enomoto, 2022). However, this method obviously cannot meet the overall race analysis for runners, and its efficacy is also low. Through object tracking in OpenCV, we can track runners and analyse aspects of their overall performance, such as pace and the distance the contestants ran during the actual competition. Using the actual coordinates, the running distance for one of the runners was calculated as follows: the 0–300 m section was 298.9 m, the 300–700 m section was 402.1 m, the 700–1100 m section was 404.6 m, and the 1100–1500 m section was 404.7 m; hence, the runner ran about 10 m more than the actual distance in the 1500 m race. Furthermore, we compared the effectiveness of target tracking and manual video analysis in calculating speeds per 100 m. According to Table 2, there was no significant difference between the two data sets ( $P = 0.23$ ), and the difference between them was less than 0.5 s. Therefore, we can conclude that using OpenCV for target tracking produces speed outputs that resemble those obtained from traditional manual methods. Jones and Whipp (2002) pointed out that, due to the influence of competition strategy and techniques, runners may travel different distances in the course of a race. For example, in their research on the actual running distance of 80 m and 5000 m runners, they pointed out that different runners have different actual running distances. This has some impact on runners' performance. Therefore, realising the tracking of runners, outputting their actual distance, and analysing their pace is of great importance to improving runners' performance in the future.

Our current research is capable of identifying and tracking 1500 m race runners, outputting their coordinate trajectory over the 1500 m distance, and calculating their speed in 100 m intervals. However, we need to further strengthen our research to conduct a more comprehensive performance analysis for the 1500 m race. For example, we need to identify the athlete's running posture and output mechanical variables such as stride frequency, stride length, joint angles, and body centre of mass data. This will enable us to go beyond the limitations of laboratory analysis and attain a more complete understanding of the sports performance of 1500 m race athletes. At present, computer vision has been used to achieve certain research findings in sports, but there are only limited applications to running events. In many sports disciplines, human pose estimation (HPE) is an important method for performance analysis and improvement of athletes. For example, Ludwig et al. (2021) taking the triple and long jump as examples, proposed two methods in their research on self-supervised learning for HPE in sports. Their evaluation results showed that training a deep neural network with a dataset containing 50 labelled images and some video sequences could generate acceptable HPE results for new sports domains. These methods have the potential to expand the use of HPE performance measurements to a wide range of sports disciplines. Previous studies have focused on tracking and evaluating soccer players' poses during competition (Bridgeman et al., 2019) and detecting the landing, jumping, and stride events of long jumpers (Einfalt et al., 2019). In addition, flight parameters of ski jumpers, such as ski angle, lower body angle, and upper body angle, have been used to improve their body posture during the flight phase and achieve long-distance flight (Ludwig et al., 2021; Bao et al., 2022). Moreover, HPE has been used to predict the landing point of the serve for table tennis players (Wu & Koike, 2020). However, there is almost no application of HPE to track and field competitions, such as sprinting and long-distance running. Thus, to further our research, we plan to identify and output mechanical variables related to athlete posture after achieving the tracking of race athletes. This will enable us to implement posture tracking and evaluation for runners during their performances. Ultimately, our aim is to contribute to the development of HPE and computer vision techniques for sports performance analysis in track and field competitions.

## Conclusion

In recent years, the development of object detection and tracking technology has given great attention to athlete tracking and recognition in video. Practise and research show that the introduction of digital video technology in sports training is conducive to improving training efficiency. The detection and tracking of athletes in videos as a non-contact method has been widely studied and applied in basketball, football, swimming, and volleyball, among other sports. However, there has been little research on the detection and tracking of track and field athletes in videos. This study, through HD video shooting, takes middle-distance 1500 m race videos as the research object and uses OpenCV to realise the recognition and tracking of runners in a

1500 m race video. We calculated the actual distance the contestant ran by obtaining coordinates and compared the effectiveness of object tracking and manual video analysis in calculating speed per 100 m ( $P = 0.23$ ) in a 1500 m race. This study is the first to use OpenCV to track middle-distance 1500 m runners in track and field events. Although a 1500 m runner was tracked throughout the race, many difficulties were encountered in the actual tracking process. The biggest difficulties were that the track and field ground was too big, the runner images in the video were too small, and the ground was complex and changeable, so too many factors affected object tracking. These factors bring great challenges to the realisation of object detection and tracking. Next, we need to explore the improvement of algorithms, video shooting methods, cameras, computers, and other equipment in the future. On this basis, we will continue conducting research into middle-distance running tracking and athletes' running posture estimation, striving to break through the posture evaluation that can only be carried out in the limited space of laboratories at present and to change traditional analysis methods. Through real-time tracking of middle-distance runners, their running performance can be analysed. Therefore, this research may bring new inspiration and reference value to the automatic analysis and running performance analysis of middle-distance running videos.

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