ORIGINAL ARTICLE

How pacing patterns influence middle-distance performance: Perspectives from object tracking and oxygen uptake

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ABSTRACT

This study explores the impact of kinematic and physiological factors on middle-distance running performance to optimize training strategies. Six runners participated in experiments with three pacing patterns (F-S, Even, and S-F), monitored using a drone, camera, and tracking technology. VO_2master measured oxygen uptake, and post-race PBLa and RPE were assessed. Results showed that the Even pattern had the lowest speed variation and most consistent trajectory. The running distances for the three pacing patterns were similar: F-S (807.30 ± 0.88 m), Even (806.52 ± 0.66 m), and S-F (806.37 ± 1.63 m). Although the Even strategy required less work, the F-S pattern had lower oxygen uptake, indicating higher efficiency. Heart rate and oxygen uptake stabilized fastest in the Even pattern, while the F-S pattern led to the lowest blood lactate (15.0 ± 2.56 mmol/L). The Even pacing is optimal for consistent performance, while F-S may optimize energy efficiency. This study emphasizes tailoring pacing strategies to an athlete's profile, suggesting further research on personalized pacing to enhance performance.
Keywords: Sport medicine, Middle-distance running, Pacing pattern, Object tracking, Oxygen uptake.

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INTRODUCTION

The primary objective of pacing studies is to determine an optimal strategy that ensures both the physiological well-being of athletes and exceptional race results. However, various external factors affect performance, and the human body's involvement in sports is highly complex. Consequently, the search for an ideal pacing strategy is still in its early stages, focusing primarily on energy metabolism and the assessment of pace adjustments that can better harness physiological functions. Traditionally, pace analysis in middle- and long-distance running has relied on manual video tracking, where speed is evaluated at 100 m intervals (Matsuo et al., 1992; Enomoto et al., 2005,2006; Kadono et al.2008; Yang & Enomoto, 2022a,b). However, this method is labour-intensive, time-consuming, and does not provide a comprehensive race analysis, making it inefficient for modern sports performance evaluation. As a result, there has been a shift towards automatic video analysis, which integrates image processing, machine learning, and artificial intelligence (Sheng et al., 2020; Wang et al., 2019). This approach has found widespread applications in technical analysis, athlete tracking, and video monitoring.

Advancements in video-based detection and tracking methods have revolutionized sports analysis, enabling more accurate and faster assessments of competition processes. Traditionally, sports training relied heavily on subjective and empirical teaching methods, with coaches observing athletes' technical movements using the naked eye. While this provided useful insights, it was limited in accuracy and consistency. Moreover, the use of sensors for movement detection added unnecessary burdens on athletes and impacted their competitiveness (Ghasemzade & Jafari, 2010; Sheng et al., 2020). Laboratory-based measurements also fell short, as exercise machines could not fully replicate natural movements, and outdoor conditions were difficult to simulate.

With the rise of computer vision technology, non-contact human motion analysis has become possible, allowing for more practical and accurate assessments of athletic performance. Athlete tracking and recognition through video-based object detection and tracking have gained attention, especially with the growing interest in integrating digital video technology into sports training (Dearden et al., 2006; Xing et al., 2010; Lu et al., 2013; Manafifard et al., 2017). Although there has been extensive research on sports like basketball, football, volleyball, and swimming (Dearden et al., 2006; Xing et al., 2010; Lu et al., 2013; Manafifard et al., 2017; Victor et al., 2017; Suzuki et al., 2020), limited work has been done on track and field athletes. The application of drone-based technology and automatic analysis presents unique challenges in track and field events. Middle-distance races cover large areas, and the athletes are relatively small in scale, making accurate tracking difficult. However, overcoming these challenges is crucial for advancing performance analysis in middle-distance running. Drone technology, combined with advanced computer vision techniques like OpenCV, offers promising solutions for tracking middle-distance runners, determining their actual running distance, and analysing their pacing patterns in real-time.

In middle-distance running, athletes do not maintain a constant pace throughout the race. Instead, they adjust their speed based on external conditions, physiological factors, and psychological states. These adjustments lead to the formation of specific pacing patterns, which are critical to race performance. Pacing behaviours among elite athletes vary depending on the event and the individual (Casado et al., 2021). Even small variations in pacing among top runners can have a significant impact on race outcomes (De Koning et al., 1999). Previous studies have focused on analysing performance in relation to pacing strategies, particularly on the benefits of fast-start (F-S) pacing strategies (Ariyoshi et al., 1979; Jones et al., 2008). The way in which athletes distribute their energy expenditure during a race can influence factors such as the contribution from oxidative and non-oxidative metabolic pathways, fatigue development, and ultimately, race performance itself (Foster et al., 1994). However, relatively few studies have explored how specific pacing strategies directly influence performance, especially in real-world track settings.

Most past research on middle-distance pacing has been confined to laboratory settings or single pacing pattern studies on the track. This study proposes a more dynamic approach by utilizing drone technology to capture race videos of middle-distance runners, followed by automatic video analysis using OpenCV. By tracking runners in real-time, this method can calculate their actual coordinates, running distance, and speed with higher precision. The integration of drone-based tracking in this study aims to provide a more detailed understanding of pacing patterns and their impact on performance. Tracking middle-distance runners using drone footage offers valuable insights into pacing strategies and performance analysis. This study addresses the limitations of traditional manual analysis by leveraging advanced video-based detection methods, enabling more accurate and efficient performance assessments. By investigating multiple pacing patterns and their physiological and biomechanical effects, this research contributes to the growing body of knowledge on optimal pacing strategies in middle-distance running.

METHODOLOGY

Participants

Six healthy male endurance athletes (1500 m runners) [20.5 ± 0.76 years; 1.74 ± 0.06 m in height; Weight: 62.1 ± 8.23 kg; Body fat percentage (%):9.32 ± 2.16; Resting blood lactate concentration (BLa): 1.5 ± 0.31mmol/L; Maximal oxygen uptake:62.07 ± 1.62ml/kg/min; Maximum heart rate:186.67 ± 5.34bpm; Personal best record for running 1500 m(PB): 239.99 ± 5.14 s] volunteered and gave written informed consent to participate in this study. This study was approved by the University of Tsukuba ethics committee (体023-104). All participants were professional middle-distance runners at the University of Tsukuba (see Table 1 for details).

Table 1. Characteristics of participants.

No.	Age (year)	Height (m)	Weight (kg)	Body fat percentage (%)	Bla (mmol/L)	$\dot{V}O_{2max}$ (ml/kg/min)	Hr_{max} (bpm)	PB1500 (s)
1	20	1.60	49.7	6.4	1.3	62.3	183	240.50
2	22	1.80	62.9	8.7	1.5	58.9	190	240.74
3	20	1.73	58.5	9.0	1.1	63.4	180	238.65
4	20	1.80	63.9	9.6	1.2	61.2	195	240.20
5	21	1.81	77.3	13.6	2.0	63.4	182	231.09
6	20	1.72	60.0	8.6	1.7	63.2	190	248.74
Mean	20.50	1.74	62.10	9.32	1.47	62.07	186.67	239.99
SD	0.76	0.07	8.23	2.16	0.31	1.62	5.34	5.14

Experimental design

This experiment was conducted on a standard 400 m track and field ground, with each athlete completing three 800 m pace runs (Pace is determined based on their 1500 m running speed.). Prior to the experiment, athletes received a detailed explanation of the procedures and were required to sign a consent form indicating their agreement and understanding of the experimental procedures. Three patterns of pace were set: Fast-Slow pacing pattern (F-S: The first 400 m is fast, and the last 400 m is slow), Even pacing pattern, and Slow-Fast pacing pattern (S-F: The first 400 m is slow, and the last 400 m is fast), with speed controlled by transmitting sound every 50 m. Running speeds were determined in consultation with the athletes, and the order of the runs was randomized. During the runs, athletes were equipped with a portable expired gas analyser (VO_2master MW-1100, Canada) to measure dynamic oxygen uptake changes during exercise. A Polar heart rate sensor (H10, Finland) to monitor heart rate fluctuations. After each run, the lactate value was measured, and the RPE value (rate of perceived exertion) was recorded. Peak blood lactate concentration (PBLa) was measured using fingertip blood collection (Lactate Pro 2; Japan; measurement range 0.5-25.0 mmol/L; measurement time 15 seconds). Blood collection occurred at 1, 3, and 5-minute intervals after the race until the runner's blood lactate concentration began to decrease. The interval between test runs was at least 30 minutes, with lactate testing conducted before each test run. We decided that the lactate concentration should be less than 4 mmol/L before the next test run. Athletes' feedback was considered, and if they felt able, they proceeded with the next test run even if the lactate concentration was over 4 mmol/L. At the same time, we recorded all the test runs on video. To track the coordinates of the runners and calculate the actual distance and real-time changing speed of the run, we used a drone (MAVIC3-CLASSIC, DJI, China) to capture the motion process of all contestants (4K,29.97fps). The drone flight was authorized by Japan's Ministry of Land, Infrastructure, Transport and Tourism (東空運航第27987号), as well as the University of Tsukuba (第23.24号). Additionally, a single digital video camera (HC-VX908M, Panasonic, Japan) was positioned at the top of a building beside the track, with panning to follow the runners. The camera recorded at a speed of 59.94 fps, saving the footage in MP4 format. We marked the track every 50 m in advance. The frame size was analysed by video analysis software to calculate the elapsed time and average running speed at 50 m sections (Figure 1).

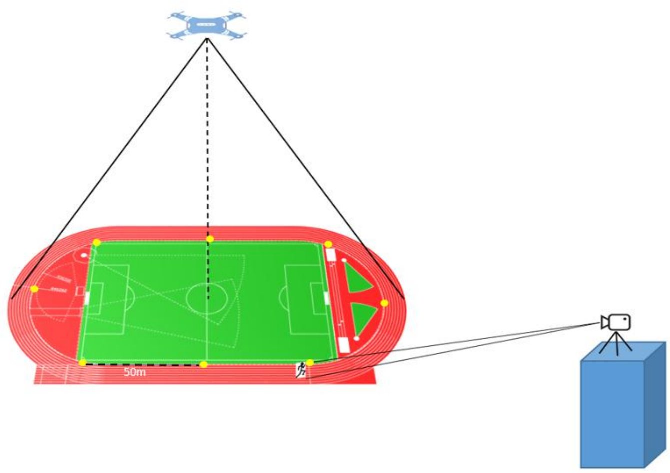

Figure 1. Drone and camera photography diagram.

Tracking algorithm, coordinate calibration and data calculation and processing

In this study, we utilized the Correlation Single-Object Tracking (CSRT) algorithm to track runners in drone footage. The CSRT tracker was chosen due to its high accuracy and its capability to track small targets in high-definition videos. It demonstrated strong performance across various target types, motion patterns, and image backgrounds. The CSRT algorithm operates by using a template to represent the target being tracked. In each frame, the tracker applies correlation filtering to identify regions matching the template and determines the best-matching region as the target's current position. The template is updated dynamically to reflect changes in the target's appearance. The CSRT algorithm employs a discriminative correlation filter framework, designed to distinguish between the target object and the background. In previous work, we successfully tracked 1500 m runners during a competition (Yang et al., 2023). We enhanced the original algorithm to improve tracking performance and accurately output image coordinates. Figure 2 demonstrates the tracking results.

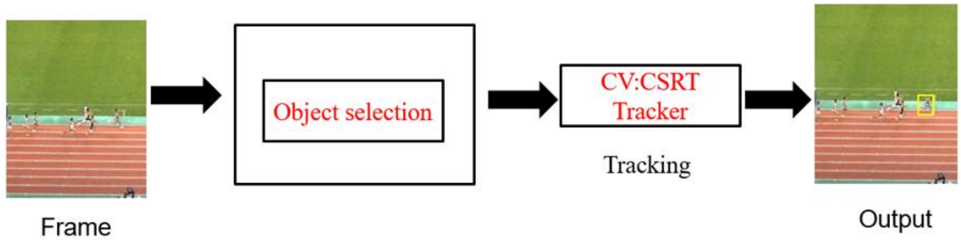

Figure 2. Structure of the object tracking method.

Figure 3. The effect of detecting and tracking a runner from drone video, and Image points for calibration.

For image calibration, we surveyed the track and field grounds prior to the running to determine precise coordinates. AutoCAD was employed to draft the track layout and measure coordinates (Yang et al., 2023). The track was a standard 400 m oval with eight lanes. The two semicircles had a radius of 37.9 m, while the straight sections measured 80 m in length and 75.8 m in width. The outer edge of the starting line for lane eight of the 110 m hurdles served as the origin point (0, 0) (Figure 3). For image-to-actual coordinate calibration, we selected 13 specific points on the track (shown in Table 2, Figure 3) and applied the Direct Linear Transformation (DLT) method to align the image coordinates with real-world coordinates. Regarding the calculation of position coordinates, the 2D DLT method (Walton, 1981) was employed. This technique establishes the relationship between image coordinates and real-world coordinates, allowing for accurate positioning of points on a 2D plane from camera images. The process involves two key steps: (1) calibration using multiple reference points (with known positions) to determine the camera's internal and external parameters, and (2) coordinate transformation, wherein DLT equations are constructed based on the 2D pixel coordinates of the reference points and their corresponding real-world coordinates. The DLT equations are then solved to derive transformation coefficients (DLT coefficients), which are subsequently used to calculate the 2D coordinates of unknown points on the image (Walton, 1981; Abdel-Aziz et al., 2015).

To reduce noise in the data, we first reduced the video frame rate from 29.97 fps to 14.99 fps, followed by data smoothing. To further refine the accuracy of the tracked data, we applied a Butterworth low-pass filter (MATLAB) with a cutoff frequency of 3 Hz to remove high-frequency noise (Winter et al., 1974). With this precise correction of coordinates, we accurately calculated the athletes' running distances and speeds, providing reliable measurements. This comprehensive approach significantly improves both the accuracy of the tracking system and the quality of data analysis in sports performance research.

Table 2. Corresponding points between image and actual coordinates.

Points	Actual points		Image points	
	X-coordinate	Y-coordinate	X-coordinate	Y-coordinate
1	110	9.76	2678	1928
2	147.77	44.54	3444	1202
3	129.2	80.3	3105	432
4	110	85.56	2723	301
5	80	85.56	2080	268
6	40	85.56	1424	250
7	30	85.56	1010	250
8	-7.9	48.07	275	1027
9	-2.8	28.68	357	1427
10	20.2	11.08	778	1823
11	30	9.76	968	1865
12	60	9.76	1595	1909
13	100	9.76	2461	1930

Note. The table illustrates the calibration of coordinate points for a video capturing a runner finishing a race. While the actual coordinates remain fixed, the image coordinates need to be extracted from each captured video frame.

Calculation of running speed and distance

To calculate the actual running distance, we used the following formula (Equation 1), based on the calibrated coordinates:

$$\mathrm{D} = \sqrt{(\mathrm{x_n} - \mathrm{x_{n-1}})^2 + (\mathrm{y_n} - \mathrm{y_{n-1}})^2} \text{ .... (Equation 1)}$$

Here, D represents the distance between two points, and x_n and y_n are the coordinates at different times n and n-1.

The runner's speed can be calculated using the following formula (Equation 2):

$$\mathrm{v} = \sqrt{\mathrm{v_x^2} + \mathrm{v_y^2}} \text{ .... (Equation 2)}$$

Where:

$\mathrm{v_x} = (\mathrm{x_n} - \mathrm{x_{n-1}}) * 14.99\mathrm{fps}$,

$\mathrm{v}_y = (\mathrm{y_n} - \mathrm{y_{n-1}}) * 14.99\mathrm{fps}$.

In this calculation: v_x and v_y represent the horizontal and vertical speed components, respectively.

v is the total speed of the runner. By using these equations, we can accurately measure both the distance covered and the speed of the runner in each video frame.

Using kinetic energy to calculate power. We can use kinetic energy divided by time to calculate instantaneous power. Power is defined as the rate at which energy changes over time, and the rate of change in kinetic energy can represent power.

To calculate instantaneous power, over a short time interval, we can use the change in kinetic energy:

$$P = \frac{\Delta KE}{\Delta t} = \frac{\frac{1}{2}m\left(v_f^2 - v_i^2\right)}{\Delta t} \text{..(Equation 3)}$$

Where:
P is the power; ΔKE is the change in kinetic energy; Δt is the time interval; v_f is the velocity at the end of the time interval; v_i is the velocity at the beginning of the time interval.

For *n* speeds, the total speed variation *Δv*, calculated using the absolute values of all adjacent speed changes, can be expressed as:

$$\Delta v = \sum_{i=1}^{n-1} |v_{i+1} - v_i| \text{...................................... (Equation 4)}$$

Here, $v_1, v_2, \ldots, v_n$ are the *n* speeds. This formula represents the sum of the absolute values of the differences between each pair of adjacent speeds.

Statistical analysis
This study used SPSS and Excel for statistical analysis. Results are presented as mean ± standard deviation (±SD). The Shapiro-Wilk test was used to assess normality, and homogeneity of variance was tested. For data meeting normality and homogeneity assumptions, one-way ANOVA was conducted, followed by LSD post hoc tests if significant differences ($p < .05$) were found. For non-normal data or unequal variances, the Mann-Whitney U test was applied. The significance level was set at .05.

RESULTS

Figure 4 shows the image coordinates (top, black lines) obtained from tracking the videos of a runner during three different-paced 800 m runs (Fast-Slow: F-S; Even; Slow-Fast: S-F) taken by a drone and the actual tracking coordinates (bottom, grey lines) calibrated from the image coordinates. We output the image coordinates of the six runners, calibrated these coordinates, and then obtained the actual running coordinates of the runners. This allowed us to calculate their running speed and distance. In our calculations of the coordinates output after tracking six runners, we found the distances for three different 800 m pacing patterns to be as follows: the F-S pacing pattern at 807.30 ± 0.88 m, the Even pacing pattern at 806.52 ± 0.66 m, and the S-F pacing pattern at 806.37 ± 1.63 m, with the distance for the F-S pattern being slightly shorter (Table 3). However, there were no significant differences in distances among the three pacing patterns. Therefore, regardless of the pacing pattern, the distance run by the runners is almost equal in the absence of special circumstances.

Table 3. Actual distance covered by runners at different paces after object tracking.

Runners	F-S(m)	Even(m)	S-F(m)
1	807.46	805.30	806.31
2	807.71	807.42	804.73
3	808.36	806.64	806.66
4	808.02	806.93	803.99
5	806.09	806.66	808.70
6	806.14	806.17	807.83
Mean	807.30	806.52	806.37
SD	0.88	0.66	1.63

Note. No significant difference in all groups.

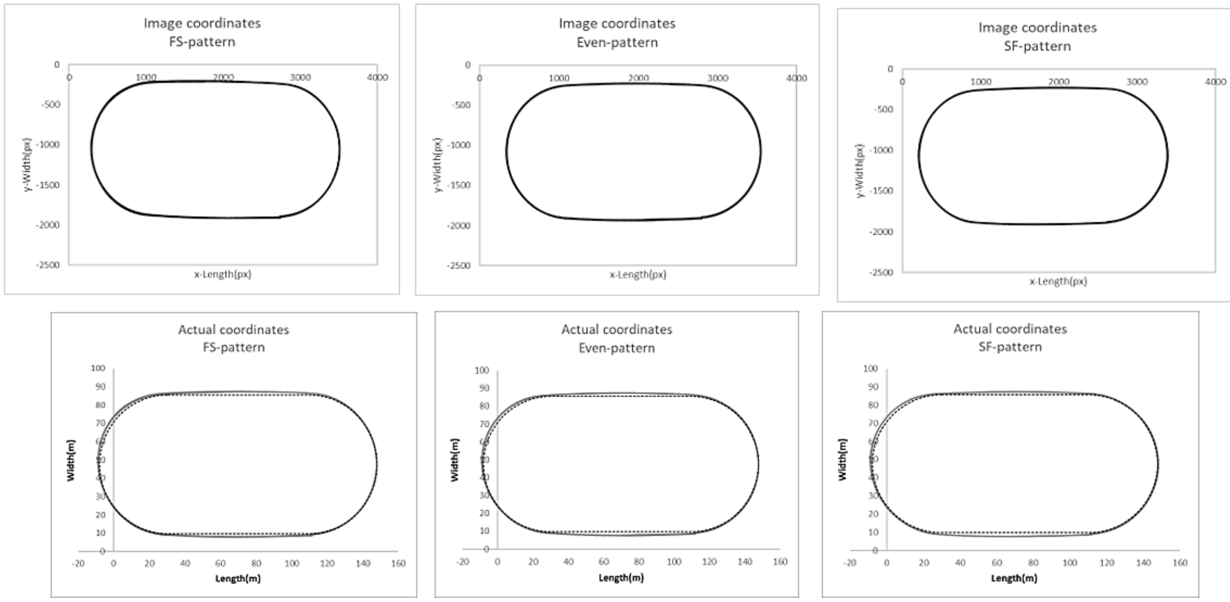

Figure 4. Tracked image coordinates of a runner (top) and actual tracked coordinates after calibration from the image coordinates (bottom). (The dotted lines represent the inner edge of the playground).

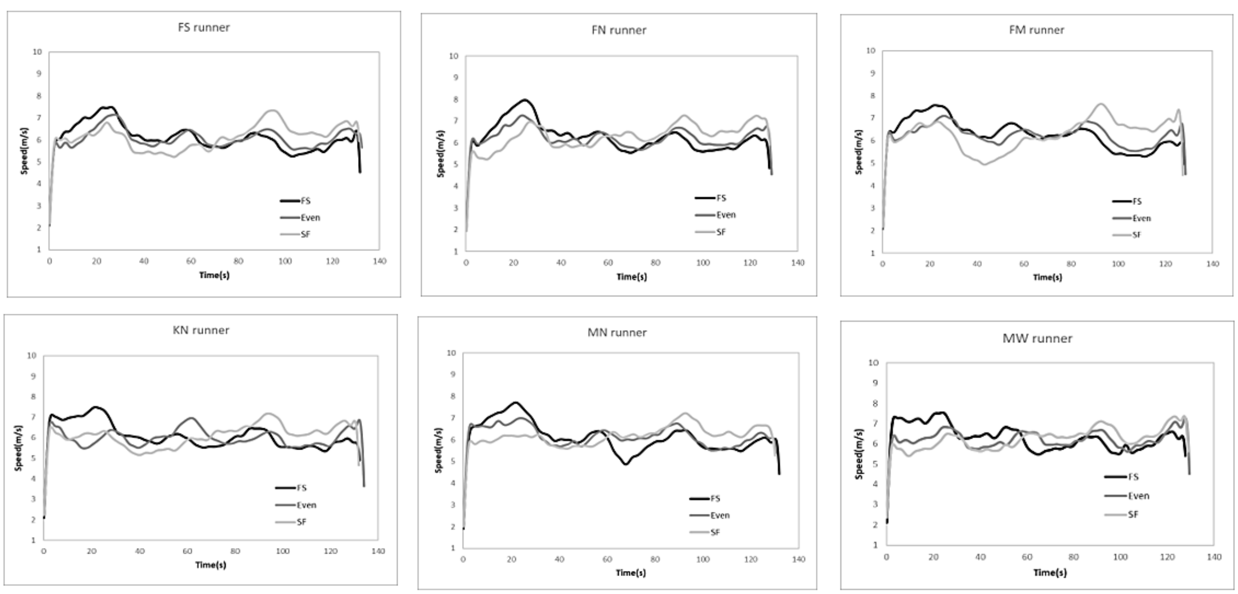

Figure 5. Changes in speed after tracking the six runners.

By tracking middle-distance runners, we can output their coordinates and subsequently calculate all speed variations. Figure 5 shows the speeds calculated from the actual coordinates of six runners after tracking their three different pacing patterns. It is evident that after an initial acceleration of 2 seconds, the speed variations display three distinct pacing patterns: F-S, Even, and S-F. In terms of acceleration, the initial acceleration of the F-S pacing pattern is significantly higher than that of the Even and S-F pacing patterns, with the F-S pacing pattern quick start pattern showing obvious acceleration deceleration. Conversely, in the S-F pacing pattern among the six runners, the acceleration of five of them is slower than that of the F-S and

Even pacing patterns. This change in acceleration and the momentary variation in speed during motion cannot be detected using traditional manual video analysis methods.

Table 4 presents the calculated total speed variations after tracking the six runners. In order to exclude the impact of acceleration and deceleration at the beginning and end on the overall data, we excluded the first 50 m and the last 50 m of the race. Among the different pacing patterns observed, the F-S pacing pattern exhibits the highest average total speed variation. The average values of the total speed variation for the Even (7.13 ± 0.54) and S-F (7.13 ± 0.72) pacing patterns are nearly identical. There is no significant difference in total speed variation among the three pacing patterns observed across the six runners.

Table 4. Total speed variation Δv for runners.

Runners	**F-S**	**Even**	**S-F**
1	8.41	7.29	7.12
2	8.18	6.75	5.87
3	6.43	8.00	6.52
4	6.08	6.28	7.70
5	7.55	7.03	7.67
6	7.09	7.43	7.87
Mean	7.29	7.13	7.13
SD	0.85	0.54	0.72

Note. No significant difference in all groups. In order to reduce the impact of acceleration and deceleration at the beginning and end of the race, we excluded the first 50 m and the last 50 m of data.

As per the work-energy theorem, the work done is equivalent to the change in kinetic energy. Table 5 shows that the Even pacing pattern required the least work, followed by the F-S pacing pattern, while the S-F pacing pattern required the most. Although the differences were not statistically significant, this trend suggests that the Even pacing pattern may help conserve energy and improve endurance and efficiency during a race.

Table 5. Total work calculated based on changes in running speed during the race.

Runners	**F-S**	**Even**	**S-F**
MW	4.408×10^3	4.414×10^3	3.900×10^3
MN	4.979×10^3	4.212×10^3	3.776×10^3
KN	4.497×10^3	4.521×10^3	4.929×10^3
FM	5.308×10^3	6.190×10^3	7.092×10^3
FN	5100×10^3	5.052×10^3	4779×10^3
FS	4.487×10^3	4.142×10^3	4.501×10^3
Mean	4.797×10^3	4.755×10^3	4.830×10^3
SD	347.21	705.98	1096.58

Note. Based on the work-energy theorem, work equals the change in kinetic energy.no significant difference in all groups.

Moreover, depending on the running speed, the dynamics of heart rate (HR) and oxygen uptake ($\dot{V}O_2$) during the running process also differ. Figure 6 illustrates the dynamic changes in speed, HR, and $\dot{V}O_2$ across different sections under various running pacing patterns. It is evident that as the initial speed accelerates, HR and $\dot{V}O_2$ in any pacing pattern exhibit an upward trend before stabilizing. Analysing the HR changes across the three different pacing patterns, the HR rise slope after acceleration is steeper for both the F-S and S-F pacing patterns, while it is relatively smaller for the Even pacing pattern. After HR stabilizes and until the end of the race, the HR of the F-S and S-F pacing patterns remains higher than that of the Even pacing pattern. During running, there was no significant difference in HR between each pacing pattern.

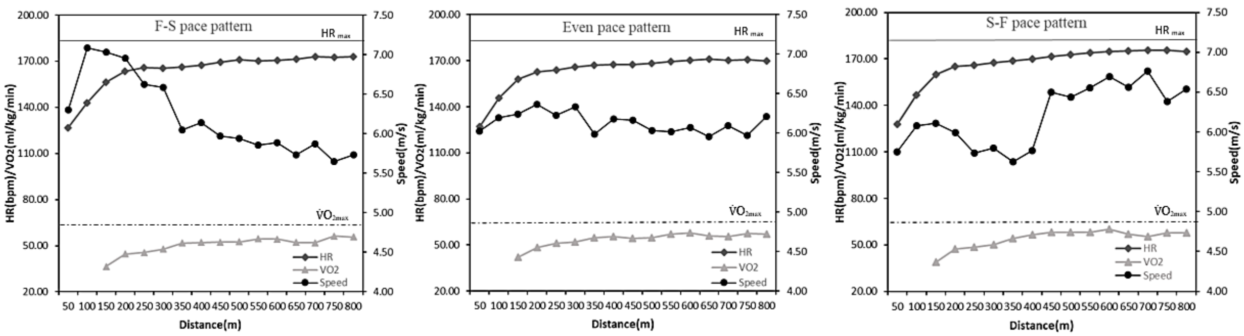

Figure 6. Changes in running speed, HR, and V̇O2 across different sections in three pacing patterns.

Additionally, when analysing the runners' PBLa, RPE, and race times, Table 5 shows that the F-S pacing pattern had the lowest PBLa (15.0 ± 2.56 mmol/L), while the S-F pacing pattern had the highest (15.9 ± 1.86 mmol/L), with the Even pacing pattern in between (15.2 ± 2.01 mmol/L). There were no significant differences in PBLa values among the three patterns. For RPE, the F-S pacing pattern had the highest average, though again, there were no significant differences between the three patterns. Four out of six participants found the F-S pacing pattern the most uncomfortable, while two found the Even pacing pattern uncomfortable, suggesting that the F-S pacing pattern has a stronger psychological impact. The average RPE scores were around 16 for all pacing strategies. The average race times were 130.00 ± 1.96 s for F-S, 130.71 ± 1.93 s for Even, and 129.68 ± 1.49 s for S-F, with no significant differences in times. Interestingly, although the runners completed the same distance in almost the same time across the three pacing strategies, their metabolic responses and psychological perceptions differed slightly, despite no significant differences between the pace patterns.

Table 6. The peak blood lactate, RPE and race time after different paces.

No.	PBLa(mmol/L)			RPE			Race time(s)		
	F-S	Even	S-F	F-S	Even	S-F	F-S	Even	S-F
1	15.5	17.8	18.5	14	17	17	127.79	129.50	129.01
2	15.4	15.7	16.5	18	17	17	131.87	130.53	130.11
3	12.8	12.9	12.5	17	17	15	132.30	134.08	131.72
4	11.3	12.9	15.1	15	17	17	128.19	128.66	127.71
5	15.5	14.2	15.8	17	15	16	128.16	129.10	128.23
6	19.5	17.6	17.1	17	14	15	131.66	132.37	131.30
Mean	15.0	15.2	15.9	16.3	16.2	16.2	130.00	130.71	129.68
SD	2.56	2.01	1.86	1.37	1.21	0.90	1.96	1.93	1.49

Note. No significant difference in all groups.

DISCUSSION

Traditionally, analysing middle-distance running competitions involves manually reviewing videos to calculate speeds over each 100 m segment (Matsuo et al., 1992; Enomoto et al., 2005,2006; Kadono et al.2008; Yang & Enomoto, 2022a,b). However, this process is time-consuming and doesn't offer a complete performance analysis. While athletes can wear sensors to track their movements more accurately, this adds extra strain and can affect their performance (Ghasemzade & Jafari, 2010; Sheng et al., 2020). Additionally, lab-based measurements are limited as fitness equipment cannot fully replicate outdoor conditions or natural movement. Video-based detection and tracking offer a faster and more precise way to analyse races. With the advancement of artificial intelligence, we can now perform this complex task using deep learning. Based on object detection, recognition, and tracking, we have developed a new method for video analysis and validated the feasibility of this method (Yang et al.,2023).In this study, we use a target detection algorithm to measure athletes' instantaneous speeds (Figure 5) and calculate their actual running distance (Table 3), introducing a more efficient method for performance analysis in middle-distance running competitions.

Figure 7 illustrates the interval speed (50m) from object tracking and manual video analysis for different runners in various pacing patterns. The black lines represent the interval speed from object tracking, while the grey lines indicate the interval speed from manual video analysis. A comparison of the speeds from object tracking and manual video analysis for all runners shows no significant difference between the two methods across different pacing patterns. Our previous research (Yang et al., 2023) also found no significant difference between the speeds from object tracking and manual video analysis when tracking a 1500 m race. Thus, object tracking proves to be effective in analysing speed in middle-distance running, and it can serve as a new method for performance analysis in such races. In addition, a larger total speed variation indicates greater speed fluctuation. Among the different pacing patterns, the Even pacing pattern showed a more stable running speed. However, there was no significant difference between the three pacing patterns (Table 4). Maintaining a stable speed may help reduce energy loss caused by excessive speed changes.

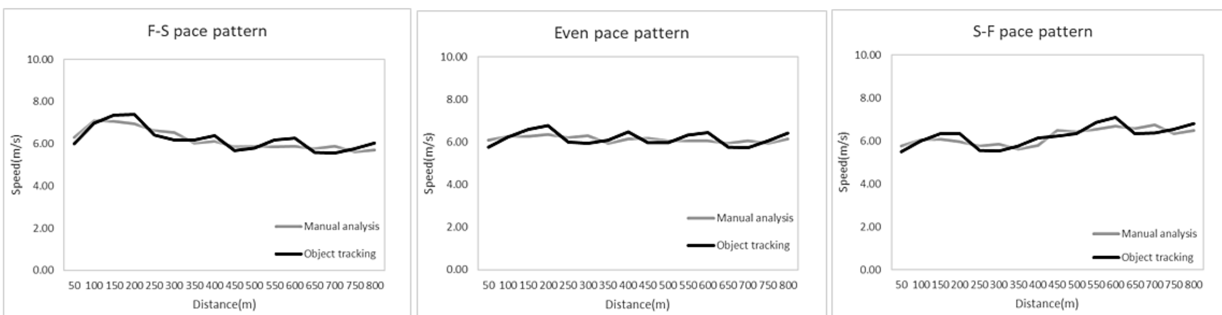

Figure 7. Average interval speed from object tracking and manual video analysis for runners with different pacing patterns.

Jones & Whipp (2002) noted that competition strategies and techniques can lead to runners covering different distances during a race. In their study on 800 m and 5000 m events, they found that athletes ran varying actual distances, which impacted performance. For example, in the Olympic men's 800 m final, Germany’s Schumann won with a time of 1:45.08, running 802 m by staying close to the kerb, while Denmark’s Kipketer, who finished second in 1:45.14, ran 813 m due to using lanes 2 and 3. Tracking athletes to measure their actual distance and pace is crucial for performance improvement. While formulas can estimate running distances, advancements in AI now allow us to track athletes using object tracking technology, providing more precise data on the distances covered. In our previous research, we tracked 1500 m runners during a race (Yang et al., 2023). The study also showed that when a runner completes an 800 m run alone, the actual distance covered remains nearly the same, regardless of different pacing strategies, with no significant differences observed between the three paces (Table 3). However, in real competitions, runners may cover greater distances due to overtaking and shifting into outer lanes. Consequently, overtaking or running in outer lanes can increase the total distance, highlighting the impact of race tactics on middle-distance performance. Running techniques and tactical decisions play a key role in influencing middle-distance running performance.

Ariyoshi et al. (1979) were among the first to analyse three pacing patterns during a 1400 m treadmill run: Fast-Slow (F-S), Slow-Fast (S-F), and Even pacing. Their study emphasized the significance of the F-S pacing pattern in middle-distance running. However, as their experiments were conducted on a treadmill, their results may not fully reflect track performance, a limitation supported by subsequent studies on oxygen uptake in running (Spencer et al., 1996; Draper & Wood, 2005; Hanon et al., 2002; Thomas et al., 2005). To address this, our study conducted pace interventions on an actual track to simulate realistic conditions. Figure 8 illustrates the oxygen uptake patterns for runners under different pacing strategies. The F-S pacing pattern showed the smallest oxygen uptake area, followed by the Even pacing pattern, and then the S-F pacing pattern. While differences in oxygen uptake values among patterns were not statistically significant, the F-S pacing pattern demonstrated higher efficiency by minimizing energy cost. Effective pacing should optimize oxygen uptake without leading to excessive anaerobic metabolism. Hanon et al. (2007) noted that an overly fast start could be detrimental and recommended an initial speed below 115% of vVO_{2max} for no longer than 25–30 s. They proposed a pacing strategy that combines a fast but controlled start, energy conservation during the middle phase, and acceleration in the final 300 m. Similarly, Jones et al. (2008) modelled pacing strategies and found Fast Start (FS) to be the most effective in reducing oxygen deficits, although this conclusion was based on theoretical research. Our findings further validated the effectiveness of the F-S pacing pattern in real-world conditions but emphasized tailoring pacing to individual athletes' characteristics. In terms of VO_2 dynamics, as shown in Figure 8, the F-S pacing pattern exhibits a slow start in oxygen uptake and a relatively low overall oxygen uptake during the race.

Additionally, Table 6 shows that the post-race PBLa, RPE, and race time values indicate that the F-S pacing pattern has the lowest PBLa (15.0 ± 2.56 mmol/L), while the S-F pacing pattern shows the highest PBLa (15.9 ± 1.86 mmol/L). The Even pacing pattern falls in between (15.2 ± 2.01 mmol/L). However, there were no significant differences in PBLa values among the three pacing patterns. From these observations, it can be inferred that in the F-S pacing pattern, runners accelerate rapidly at the beginning of the race, requiring a high energy output over a short period. During this phase, aerobic energy supply is delayed, and energy is primarily derived from anaerobic sources such as the ATP-PC system and glycolysis. The lower oxygen uptake at the start likely reflects the inability of the aerobic system to immediately provide sufficient oxygen, suggesting that anaerobic metabolism plays a significant role during this period. Furthermore, while the low lactate concentration might initially appear to indicate a limited contribution of anaerobic metabolism, it is possible that the F-S pacing pattern's strategy—reaching top speed quickly and then reducing pace—helps suppress overall energy expenditure. This efficiency may prevent excessive activation of glycolysis and the resulting accumulation of lactate.

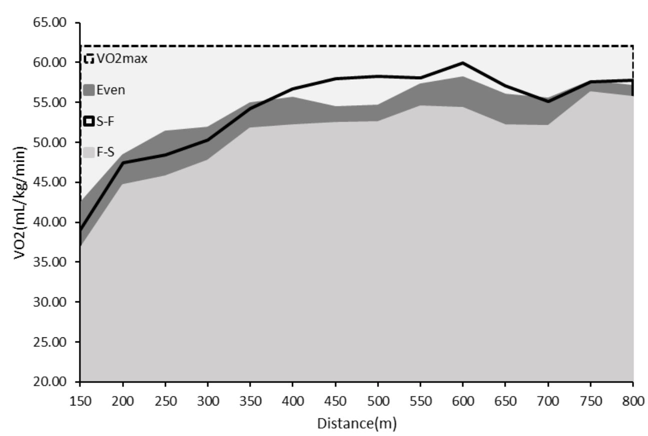

Figure 8. Dynamic changes in oxygen uptake across 50 m sections for three pacing patterns.

CONCLUSIONS

The objective of this study is to advance the understanding of how kinematic and physiological factors influence middle-distance running performance, with the goal of providing practical guidance for optimizing training strategies and improving athletic outcomes. This study investigated the physiological and kinematic effects of different pacing strategies in middle distance runners through experimental interventions on the track. The key findings are as follows:

Object tracking and kinematic analysis

The runners' speed changes and movement trajectories were tracked, showing that the Even pacing pattern had the lowest average total speed variation. The calculated distances for the three 800 m pacing patterns were: F-S (807.30 ± 0.88 m), Even (806.52 ± 0.66 m), and S-F (806.37 ± 1.63 m), with no statistically significant differences among them. The Even pacing pattern required the least work, followed by the F-S pacing pattern, while the S-F pacing pattern required the most, though these differences were not statistically significant.

Pacing and physiological metrics analysis

The F-S pacing pattern demonstrated lower oxygen uptake compared to the Even and S-F pacing patterns, indicating its efficiency in minimizing energy costs. Additionally, heart rate (HR) and oxygen uptake (VO_2) stabilized more rapidly under the Even pacing pattern, while the F-S pattern resulted in the lowest post-race blood lactate concentration (15.0 ± 2.56 mmol/L), despite no statistically significant differences across strategies. The F-S pacing pattern showed lower oxygen uptake, underscoring its efficiency in minimizing energy costs. While the Even pacing pattern demonstrated more consistent speed control, all strategies exhibited significant energy expenditure during the initial phase due to rapid kinetic energy increases. The Even pacing strategy appears more suitable for maintaining consistent performance, while the F-S pacing pattern is advantageous for optimizing energy efficiency and oxygen utilization in competitive contexts.

This study bridges theoretical research and practical application, emphasizing the importance of personalized pacing strategies based on an athlete's physiological and kinematic profile. Future research should explore individual variations in response to pacing strategies, focusing on optimizing performance through tailored interventions. This work contributes to advancing middle-distance running analysis and lays a foundation for innovative approaches in training and competition.

AUTHOR CONTRIBUTIONS

Study concept and design, drafting of the article, and critical revision: Yongchang Yang and Yasushi Enomoto. Experimental assistance and data collection: Haruka Sugawara. Computer programming: Xinwei Lee. Data collection, interpretation and analysis, final approval of the version to be published: Yongchang Yang.

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