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Algorithm-Based Real-Time Analysis of Training Phases in Competitive Canoeing: An Automated Approach for Performance Monitoring

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Abstract: The increasing demands in high-performance sports have led to the integration of technological solutions for training optimization. This study aimed to develop and validate an algorithm-based system for analyzing three critical phases in canoe training: initial acceleration, steady-state cruising, and final sprint. Using inertial measurement units (WIMU PRO™) sampling at 10 Hz, we collected performance data from 12 young canoeists at the Mar Menor High-Performance Sports Center. The custom-developed algorithm processed velocity–time data through polynomial fitting and phase detection methods. Results showed distinctive patterns in the acceleration phase, with initial rapid acceleration (5 s to stabilization) deteriorating in subsequent trials (9–10 s). Athletes maintained consistent stabilized speeds (14.62–14.98 km/h) but required increasing space for stabilization (13.49 to 31.70 m), with slope values decreasing from 2.58% to 0.74% across trials. Performance deterioration was evident through decreasing maximum speeds (18.58 to 17.30 km/h) and minimum speeds (11.17 to 10.17 km/h) across series. The algorithm successfully identified phase transitions and provided real-time feedback on key performance indicators. This technological approach enables automated detection of training phases and provides quantitative metrics for technique assessment, offering coaches and athletes an objective tool for performance optimization in canoeing. Our aim is to automate the analysis task that is currently performed manually by providing an algorithm that the coaches can understand, using very basic mathematical tools, and that saves time for them.

Keywords: biomechanics; sports technology; performance analysis; motion tracking; stroke efficiency; sports training

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1. Introduction

Canoeing, having a history of thousands of years as a means of transportation, has evolved into an extremely competitive Olympic sport that demands high physical conditioning, technical proficiency, and tactical awareness [1]. Modern competitive canoeing encompasses a number of disciplines, including sprint canoeing, slalom, and marathon races, each having different technical and physiological requirements, incorporated in the International Canoe Federation [2]. Sprint canoeing, specifically, has turned into an enormously popular sport since its introduction at the Olympic Games, which requires athletes to exhibit an all-around synthesis of strength, endurance, and technical accuracy [3]. The sport necessitates special anthropometric features and physical abilities, as a number of studies have emphasized the importance of upper body strength, aerobic fitness, and technical proficiency [4,5]. Physiological demands vary greatly across race distances, from explosive power for 200 m races to aerobic endurance for the longer distance races, with specific training modalities needed for each one [6].

Key performance indicator (KPI) analysis in the sport of canoeing has conventionally been through a combination of qualitative and quantitative approaches. Qualitative analysis generally involves expert judgment of the pattern and technique of movement, with attention to aspects such as paddle entry, pull-through phase, and recovery mechanics [7]. But inherent limitations with subjective evaluation have seen greater focus on quantitative analytical techniques. C1 sprint canoeing presents unique technical challenges compared to other paddle sports, requiring asymmetrical force application with a single-blade paddle from a kneeling position, creating distinctive biomechanical demands. These specific technical elements of C1 paddling require specialized performance metrics focused on stroke asymmetry, boat roll compensation, and powerful trunk rotation movements that are distinct from two-blade kayaking techniques [8,9]. Recent research demonstrates that competitive canoeing success is largely reliant on the integration of these parameters, most notably, the ability to sustain consistent stroke mechanics and power transmission efficiency across varying stages of the race [10,11]. The ability to accurately measure these parameters has become vital to training optimization and competition strategy development.

The use of emerging technologies has revolutionized performance analysis and training methodology in canoeing. Modern technology applications range from basic video analysis software to complex sensor-based monitoring systems [12]. GPS technology, force measurement systems, and biomechanical analysis equipment have become standard elements in elite training centers [13–15]. In C1 canoeing, specifically, inertial measurement units (IMUs) have shown particular promise due to their ability to capture the complex three-dimensional movements unique to single-blade paddling. Unlike two-blade kayaking, C1 technique involves pronounced rotational torso movements and lateral weight shifts that require specialized sensor configurations and algorithms to accurately quantify [16,17]. A point of interest is the recent innovation in the application of Inertial Measurement Units (IMUs) as an effective analysis tool for performance. The devices in question, generally composed of accelerometers, gyroscopes, and magnetometers, present various notable benefits: elevated sampling rates (commonly >100 Hz), the capacity for multi-axial movement recognition, and the functionality to amalgamate data from numerous sensors concurrently [18]. IMUs provide precise measurements of acceleration, angular velocity, and orientation, enabling detailed analysis of paddle movement patterns and body position changes throughout the stroke cycle [16,17].

Specialized signal-processing algorithms for IMU signals have opened up new avenues for movement detection and performance analysis in sports. These algorithms are capable of filtering noise effectively, identifying individual movement patterns, and extracting meaningful performance metrics from dense sensor data. In canoeing, algorithmic processing has enabled automatic identification of stroke phases, assessment of technique consistency, and identification of fatigue-related degradation of technique [19,20]. Advanced signal processing techniques and machine learning algorithms have enhanced our ability to analyze movement patterns in real time, providing immediate feedback to athletes and coaches [21,22]. This technological advancement has particularly benefited the analysis of cyclic movements in sports, allowing for more precise quantification of performance parameters and technique variations [23].

Previous algorithmic approaches for paddling analysis have primarily focused on stroke detection rather than comprehensive phase identification, with Liu et al. [17,19] using peak detection algorithms and Gomes et al. [9] employing threshold-based approaches that lack sensitivity to broader phase transitions and are susceptible to fatigue effects. Elite C1 coaching methodologies emphasize phase-specific technique requirements—powerful asymmetrical strokes during initial acceleration, balanced rhythmical patterns in steady-state cruising, and increased stroke rate with maintained efficiency during sprints—yet current training relies heavily on subjective observation rather than quantitative metrics for phase transitions, creating an opportunity for technology-enabled coaching innovations that provide real-time feedback on phase-specific performance [3,20,23].

Despite these technological advances, there remains a significant gap in our understanding of how to effectively monitor and analyze different training phases in real time during canoe training sessions. While existing research has examined isolated aspects of canoeing performance, the specific challenge of automatically identifying transition points between critical training phases in C1 canoeing remains inadequately addressed, with previous studies by Fernandes et al. [16] and Bonaiuto et al. [15] quantifying overall metrics but failing to develop real-time phase segmentation methods; our polynomial fitting approach addresses this gap by modeling acceleration curves and identifying inflection points that mark genuine phase transitions rather than relying on arbitrary thresholds. Therefore, this study aims to address this gap by developing and implementing an algorithm-based system for real-time analysis of three critical training phases in canoeing: the initial acceleration phase, the steady-state cruising phase, and the final sprint phase. We hypothesize that our custom algorithm will effectively identify and analyze these distinct phases, providing valuable insights into technique efficiency and performance variations. Furthermore, we propose that this real-time analysis system will enable more precise and timely adjustments to training protocols, ultimately contributing to enhanced performance optimization in competitive canoeing.

2. Materials and Methods

2.1. Design

This research used a cross-sectional observational design to examine the phases of canoe training aided by technological advancement. The study took place at the Mar Menor High-Performance Sports Center "Infanta Cristina" of Los Alcázares (Murcia, Spain), which is a specialized facility for the training and development of high-level athletes. The data were registered during training sessions over the course of two years, with emphasis on the evaluation of three different phases of performance: initial acceleration, steady-state cruising, and final sprint.

2.2. Participants

Young Spanish national team canoeists who were training to be professional athletes to compete in international competitions (European Championships, World Championships, and the Olympics) participated in the study. All participants were single-person canoe (C1) specialists, competing and training exclusively in this Olympic discipline. All athletes were actively training at the High-Performance Center under the supervision of the Spanish Canoeing Federation. For consideration, the participants were required to fulfill the following criteria: (1) they must be an active national team member, (2) they must have at least three years of competitive experience, and (3) they must not have any injury that might impair performance.

The sample consisted of 12 athletes (8 males and 4 females; age: 15.7 ± 0.7 years; height: 176.3 ± 7.2 cm; body mass: 72.4 ± 8.3 kg; competitive experience: 5.6 ± 1.8 years). While our sample included both male and female athletes, gender was not a relevant variable for this study, as our primary aim was to identify biomechanical and kinematical variables to evaluate the phase-detection algorithm's mathematical functionality across different velocity profiles rather than to compare performance outcomes between genders. The procedures of the study were explained to all participants, and they provided written informed consent before participation. In the case of athletes younger than 18 years, parental consent was also obtained. The research was carried out in accordance with the Declaration of Helsinki and was authorized by the Ethics Committee of the University of Murcia (reference number: 3495/2021).

2.3. Equipment and Data Processing

Data collection was realized using the WIMU PRO™ device (RealTrack Systems, Almeria, Spain). The inertial measurement unit combines various sensors in a lightweight 70 g unit of 81 × 45 × 16 mm. Four 3D accelerometers with various ranges (±16 G, ±16 G, ±32 G, and ±400 G) provide thorough detection of movement at varying intensities. Three gyroscopes (two of which are ±2000°/s and one of which is ±4000°/s, both at 1000 Hz sampling) measure rotational movement, augmented by a 3D magnetometer (±8 Gauss at 160 Hz) and a barometer (±1200 mbar at 100 Hz).

To enable accurate spatial localization and speed measurements, the device uses GNSS/GPS technology at 10 Hz with a UWB positioning system at 18 Hz. Data transmission is enabled by various channels, such as WiFi 802.11 b/g/n, Bluetooth, ANT+, and USB 2.0, and all data are recorded in 8 GB internal flash memory. The 4 h battery life of the device enables efficient analysis of training sessions.

Primary data processing was performed through SPRO™ software (Version 2023.1, RealTrack Systems, Almería, Spain), which offers large-scale data analysis and the possibility to export raw data for subsequent use of custom-designed algorithms. The analysis process included generic and sport-specific software tools. Generic analysis was conducted by Microsoft Excel (Version 16.0, Microsoft Corporation, Redmond, WA, USA) and IBM SPSS Statistics (Version 28.0, IBM Corp., Armonk, NY, USA). Custom-made algorithm development and signal processing were performed with MATLAB (Version R2023b, MathWorks Inc., Natick, MA, USA).

All tests were conducted using ICF standard C1 (single-person canoe) watercraft. The canoes used in this study complied with International Canoe Federation (ICF) regulations for sprint competitions: minimum length of 5.20 m, minimum width of 0.35 m, minimum weight of 14 kg, and no rudder. Each athlete used their personal competition canoe to ensure familiarity with the equipment during testing, though all canoes met the standardized ICF specifications. These competition vessels were selected to ensure result validity specifically for C1 sprint applications, which represents one of the core Olympic disciplines in sprint canoeing.

2.4. Procedures

All testing procedures were conducted across three primary locations, each serving specific research purposes. The primary research center was established at the Faculty of Sports Sciences of the University of Murcia, specifically, within the laboratory of the Research Group E0A1-06 BIOVETMED & SPORTSCI in San Javier (Murcia, Spain). This facility served as the main center for data processing and research team meetings, equipped with necessary computational resources and analysis software.

The algorithm development and mathematical analysis were conducted at the Higher Technical School of Engineering of Roads, Canals and Ports and Engineering of the Polytechnic University of Cartagena. This facility provided the necessary technical infrastructure for developing and refining the mathematical algorithms used in the study.

Field testing and data collection were performed at the Sports Technification Center in Los Narejos (Los Alcázares, Murcia, Spain), specifically, on the beach area. Testing sessions were conducted under controlled environmental conditions (wind speed < 8 km/h, water temperature 18–22 °C) to ensure consistency in data collection. Each testing session followed a standardized protocol beginning with a 10 min device setup period, including calibration and secure placement of the WIMU PRO™ device on the kayak.

The WIMU PRO™ device was consistently positioned 40 cm from the bow of each canoe (Figure 1), securely attached using a waterproof adjustable bracket with vibration-dampening properties. This standardized position was selected to optimize data collection of forward motion parameters while minimizing interference from water splashing. The placement was identical across all participants and trials to ensure measurement consistency. Preliminary testing confirmed that this specific location provided reliable velocity and acceleration readings with minimal signal noise due to water contact or paddle stroke vibrations.

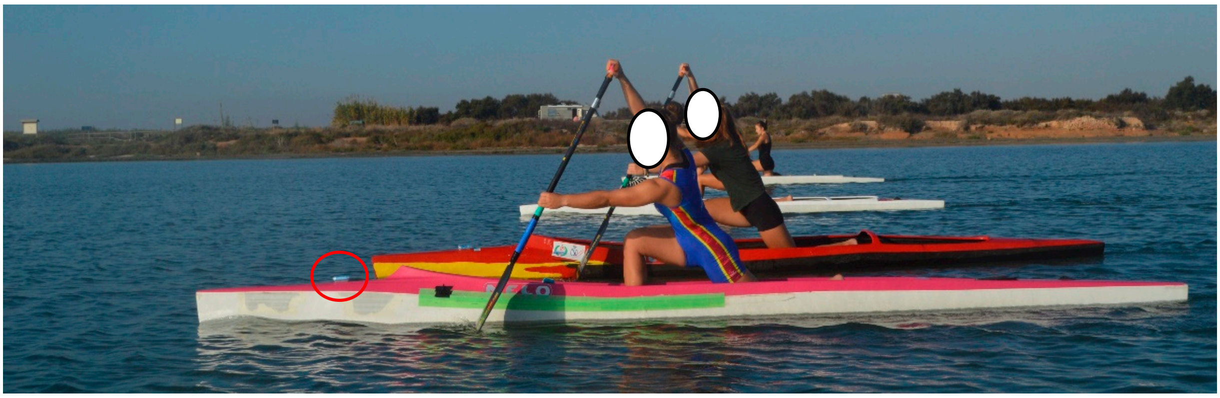


Figure 1. Standardized placement of the WIMU PRO™ device on the canoe (red circle).

Athletes completed a structured 15 min warm-up protocol, including course familiarization and equipment adjustment. The main testing protocol consisted of three maximal effort trials over 200 m, with 10 min recovery periods between trials. GPS markers were placed at start and finish points to ensure accurate distance measurement. During each trial, continuous recording of position data was maintained, with real-time monitoring of signal quality and a backup recording system for redundancy.

2.5. Signal Processing and Algorithm Development

The analysis of the collected data followed a systematic approach combining signal processing and algorithm implementation. Initial signal processing involved filtering and smoothing of the raw IMU data (10 Hz) through a moving average filter to reduce noise while preserving essential movement patterns, as shown in the comparison between raw and filtered signals in Figure 2A. The algorithm then processed this filtered data to identify the three critical performance phases through automated detection of transition points, illustrated in Figure 2B.

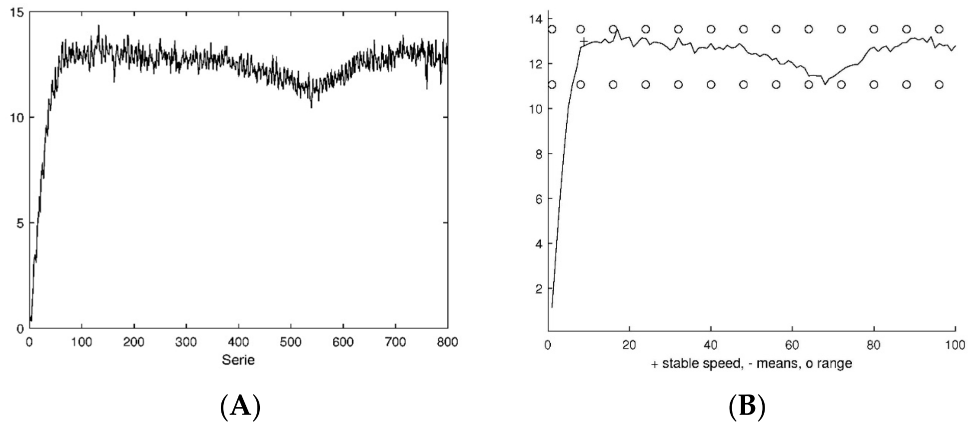


Figure 2. Signal processing stages in canoe performance analysis. (**A**) Comparison between raw velocity data (grey line) and filtered signal (black line) demonstrating noise reduction. (**B**) Phase detection analysis with identified cruising speed threshold (dashed line). Data collected using WIMU PRO™ device at 10 Hz sampling frequency.

Then, for the algorithm development, we focused on the detection and analysis of three critical phases in canoe performance: initial acceleration, steady-state cruising, and final sprint. The steps that we propose for our own algorithm are the following:

Step 1: smoothing the signal considering means in subintervals.
Step 2: define the cruising speed as the mean of the first speed, where the smoothed signal decreases, and the two consecutive means.
Step 3: compute the local maximum and minimum.
Step 4: compute the range as the interval between the absolute maximum and the absolute minimum.
Step 5: Construct the best-fit polynomial (in a least-squares sense) for the data in the interval $[0, t_s]$, where t_s is the time where the speed is stabilized (Step 2). Compute the average of the slope of the polynomial. We consider the first-order polynomial, since a line reproduces the behavior of the signal in the first phase, but the algorithm can use second-order polynomials.

We refer to Appendix A at the end of this paper, for a pseudocode explanation of these steps.

2.6. Phase Division Criteria

In canoe performance, three critical phases can be distinguished throughout a race or training session: the initial acceleration, the steady-state cruising phase, and the final sprint. The initial acceleration occurs at the start, where the athlete generates powerful strokes to overcome inertia and quickly gain speed. This is followed by the steady-state cruising phase, where the paddler aims to maintain a consistent and efficient velocity using a rhythm that balances effort and endurance. Finally, the race concludes with the final sprint, during which the athlete increases the stroke rate and intensity to maximize speed and performance over the last segment of the distance. Understanding and analyzing these phases is essential for optimizing technique, pacing strategies, and overall performance.

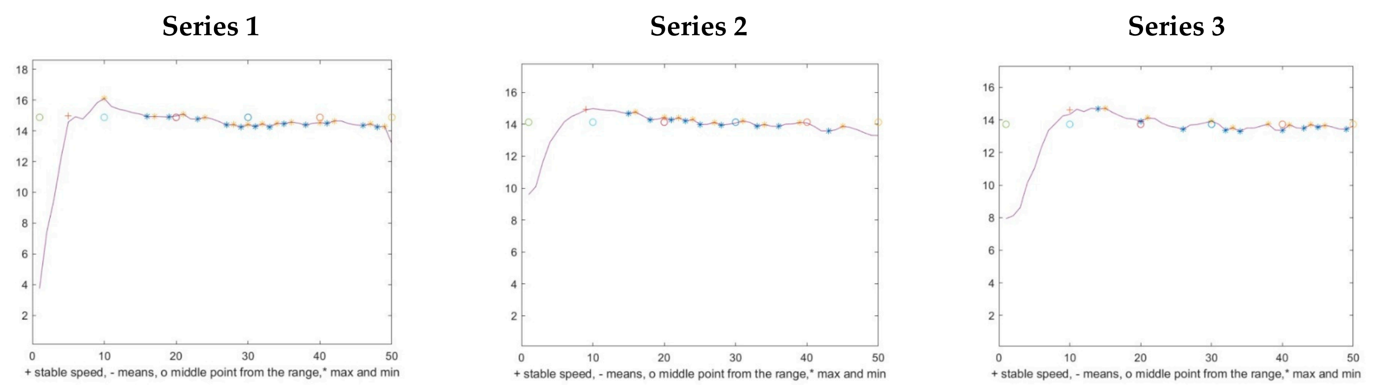
The algorithm identifies phase transitions using the following criteria (Table 1): (1) The initial acceleration phase begins at movement onset ($v > 0.5$ km/h) and continues until the first stabilization point, defined as the first point where the velocity reaches 95% of the calculated cruising speed and maintains this level (±5%) for at least 2 s; (2) The steady-state cruising phase extends from this stabilization point until the onset of the final sprint, which is identified as the point where the velocity consistently increases beyond the cruising speed by >10%, with positive acceleration for at least 1.5 s; (3) The final sprint phase continues from this point until the completion of the trial. These objective criteria ensure consistent phase identification across all participants and trials.

Table 1. Algorithm criteria for identifying phase transitions.

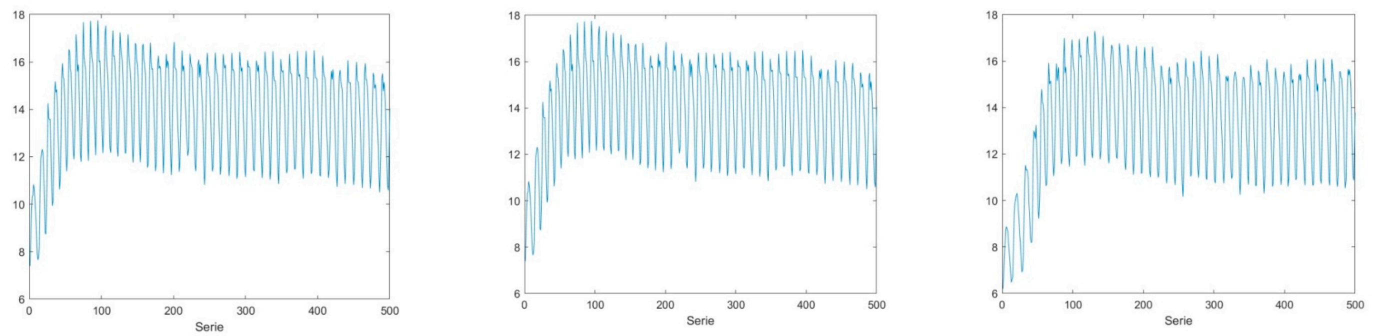
Phase	Description	Identification Criteria
Initial Acceleration	The athlete generates powerful strokes to overcome inertia and quickly gain speed	Starts at movement onset (velocity > 0.5 km/h) and continues until the velocity reaches 95% of the cruising speed and stays within ±5% for at least 2 s
Steady-State Cruising	The paddler maintains a consistent and efficient velocity with a rhythm that balances effort and endurance	Begins at the stabilization point (as defined above) and lasts until velocity increases by more than 10% over cruising speed with positive acceleration sustained for at least 1.5 s.
Final Sprint	The athlete increases stroke rate and intensity to maximize speed and performance in the final segment	Starts when the velocity increases >10% over cruising speed with sustained positive acceleration (≥1.5 s) and continues until the end of the trial

3. Results

The algorithm successfully analyzed the velocity profiles across three series, providing comprehensive visualizations for each trial. For each series, four distinct analytical representations were generated: a velocity–time profile, a velocity distribution histogram, a polynomial fit analysis, and a space–time relationship plot. These visualizations enabled detailed examination of performance characteristics across different phases of each trial (Figure 3).

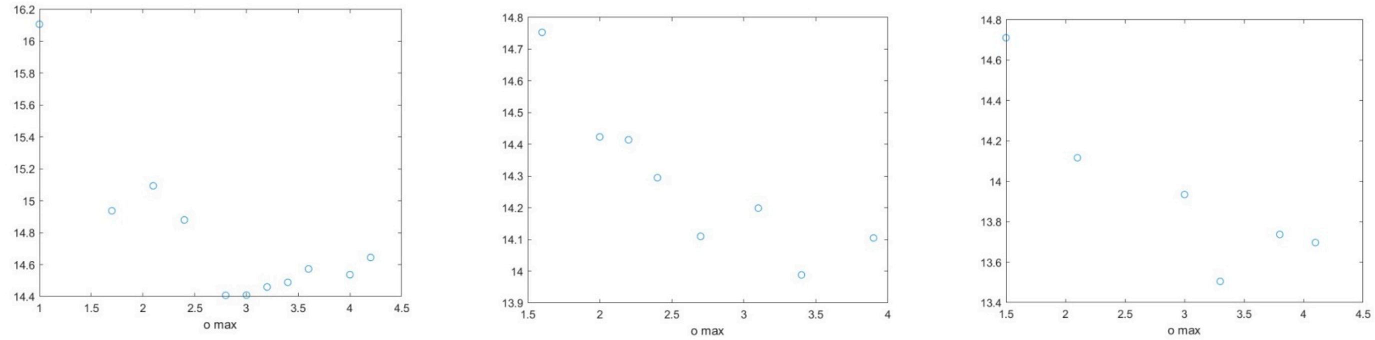


(A)

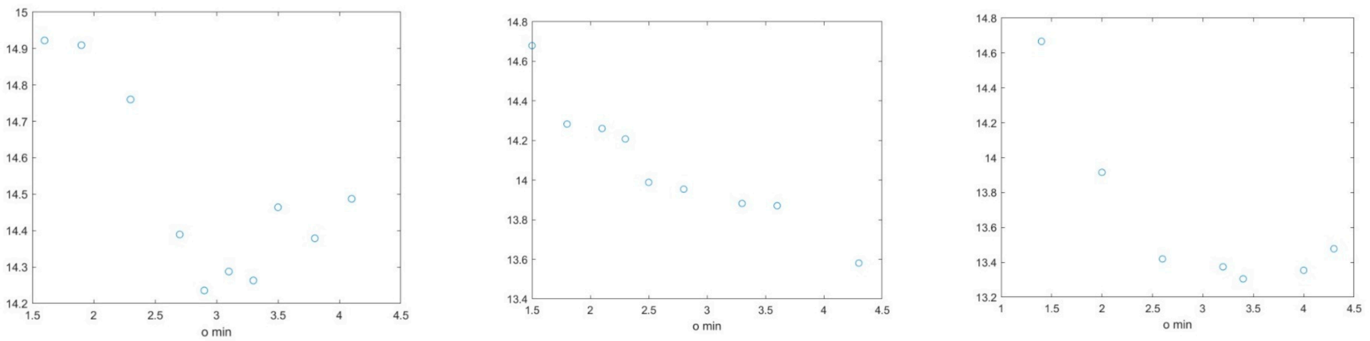


(B)

Figure 3. *Cont.*



(**C**)



(**D**)

Figure 3. Visual representation of performance analysis for each canoe trial showing four complementary analyses: velocity–time profile (**A**), velocity distribution histogram (**B**), polynomial fitting of the acceleration phase (**C**), and space–time relationship (**D**). Data presented demonstrate the characteristic patterns analyzed through the custom algorithm.

The velocity–time profiles (Figure 3A) revealed distinct performance patterns, with Series 1 demonstrating an aggressive acceleration profile and reaching peak velocities more rapidly than subsequent trials. Series 2 and 3 showed more gradual acceleration patterns, with smoother transitions between phases. The velocity distribution histograms (Figure 3B) highlighted variations in speed maintenance, with Series 1 exhibiting the widest distribution of velocities post-stabilization, while Series 2 and 3 showed progressively narrower distributions, suggesting more consistent but generally lower velocity maintenance patterns.

Polynomial fitting analysis of the acceleration phase (Figure 3C) revealed marked differences in performance efficiency between series, with Series 1 demonstrating the steepest acceleration curve, while Series 2 and 3 displayed more gradual polynomial curves. The space–time relationship plots (Figure 3D) further confirmed these patterns, clearly demonstrating the superior acceleration characteristics of Series 1, particularly in the initial phase, whereas Series 2 and 3 showed similar patterns to each other but with notably different profiles from Series 1, especially in the distance required to achieve stabilization.

Analysis of the performance parameters compiled in Table 2 revealed several significant trends across the three series. The stabilized speed showed minimal variation between series (14.98, 14.93, and 14.62 km/h, respectively), but the space required to achieve these speeds increased substantially from Series 1 (13.49 m) to Series 2 and 3 (31.39 and 31.70 m). The time until stabilized speed followed a similar pattern, with Series 1 requiring only 5 s compared to 9 and 10 s for Series 2 and 3.

The slope values recorded in Table 2 further quantified these differences, with Series 1 showing a markedly higher slope (2.58%) compared to Series 2 (0.74%) and Series 3 (0.84%). Maximum speeds after stabilization demonstrated a consistent decline across series (18.58, 17.76, and 17.30 km/h), as did minimum speeds (11.17, 10.50, and 10.17 km/h), indicating progressive performance deterioration. The real space measurements closely matched the calculated distances, with only minor discrepancies across all series, validating the accuracy of the algorithmic approach.

Table 2. Performance parameters across three series of canoe training analysis.

Series	1	2	3
Stabilized Speed (SS) (km/h)	14.98	14.93	14.62
Space until SS (m)	13.49	31.39	31.70
Real Space until SS (m)	13.85	32.44	31.87
Time until SS (s)	5.00	9.00	10.00
Slope until SS (%)	2.58	0.74	0.84
Maximum Speed after SS (km/h)	18.58	17.76	17.30
Minimum Speed after SS (km/h)	11.17	10.50	10.17

4. Discussion

The development and validation of automated analysis systems for sports performance represents a significant advancement in training optimization. This study aimed to create and implement an algorithm-based system for real-time analysis of canoe training phases, specifically focusing on the detection and characterization of initial acceleration, steady-state cruising, and final sprint phases. Our findings demonstrated the algorithm's capability to effectively identify these phases and provide quantitative metrics for performance assessment, offering coaches and athletes objective data for training optimization, which aligns with recent technological trends in water sports monitoring [12,15].

The analysis of the acceleration phase revealed interesting patterns in performance development. Athletes achieved stabilized speeds between 14.62 and 14.98 km/h, which are higher values than previously reported for elite kayakers [8,10]. The time required to reach a stabilized speed varied considerably between series (5–10 s), suggesting significant differences in acceleration strategies and fatigue effects across trials. This variability in acceleration profiles might be attributed to different technical approaches or physical capabilities, as suggested by recent biomechanical analyses [9,11]. The importance of this initial phase has been highlighted in previous research, where proper technique during acceleration has been shown to significantly impact overall performance [3,24].

The steady-state phase analysis provided particularly valuable insights into technical consistency. The velocity fluctuations observed between maximum and minimum speeds after stabilization (ranging from 7.41 km/h in Series 1 to 7.13 km/h in Series 3) indicate varying levels of velocity maintenance capability across trials. This finding aligns with research by Gomes et al. [25], who emphasized that successful performance in competitive canoeing relies heavily on the optimization of stroke parameters and efficiency metrics. The progressive decrease in both maximum and minimum speeds across series (from 18.58 to 17.30 km/h for maximum speeds and from 11.17 to 10.17 km/h for minimum speeds) suggests a systematic impact of fatigue on performance [24,26].

The slope analysis during the acceleration phase revealed significant variations between series (from 2.58% in Series 1 to 0.74–0.84% in Series 2 and 3), introducing a novel metric for evaluating acceleration efficiency. This parameter, calculated through polynomial fitting, provides a quantitative characterization of acceleration patterns that complements traditional time-based metrics [16,19]. The marked difference in slope values between the first and subsequent series suggests a substantial impact of fatigue on acceleration capability, potentially reflecting changes in technical execution and power output [27,28].

Performance deterioration across series was particularly evident in the increasing space required to achieve a stabilized speed (from 13.49 m in Series 1 to over 31 m in Series 2 and 3). This degradation in performance aligns with previous research on fatigue effects in elite canoeists [29,30]. The relationship between higher cruising speeds and poorer final sprint performance has also been documented in recent studies [8,10], suggesting the need for specific training interventions focused on maintaining power output throughout the entire performance [6].

The implementation of IMU-based analysis provides several advantages over traditional assessment methods, as highlighted by recent technological developments [17,18]. The high sampling frequency and multi-axial movement detection capabilities allow for more precise quantification of performance parameters, representing a significant advancement from traditional video analysis methods [15,31]. Our approach of combining velocity–time profiles, distribution histograms, polynomial fitting, and space–time relationships provides a comprehensive framework for performance analysis that captures both macro and micro aspects of technique execution.

Several limitations should be considered when interpreting these results. First, the relatively small sample size ($n = 12$), although typical for elite sports research, may limit the generalizability of findings. Second, environmental conditions, while controlled, could still influence performance parameters. Third, our original intention to integrate the algorithm directly into the inertial device for true real-time implementation was not realized due to changes in the commercial partnership that supported the technology development; however, the current implementation demonstrates robust phase detection with minimal processing delay. Fourth, the current algorithm relies solely on GPS velocity data, which may be subject to accuracy limitations and potential signal degradation in certain environments. GPS measurement errors could affect the precision of phase detection, particularly when velocity changes are subtle. Additionally, the algorithm does not yet incorporate data from the available inertial sensors (accelerometers, gyroscopes), which could potentially enhance phase detection accuracy by capturing stroke-specific movement patterns that complement velocity data. Future research could integrate multiple sensor inputs to increase robustness against GPS signal variations and provide redundancy in measurement, as well as expanding the sample size, incorporating different skill levels, and investigating the algorithm's applicability across various environmental conditions. Additionally, longitudinal studies examining the relationship between these performance metrics and competition outcomes would provide valuable insights into the predictive validity of the analysis system. The integration of machine learning approaches could further enhance the algorithm's capabilities in pattern recognition and performance prediction.

5. Conclusions

This study demonstrated the effectiveness of a novel algorithm-based system for analyzing three critical phases of canoe performance in real time. Our analysis revealed significant performance patterns across multiple trials: rapid initial acceleration in Series 1 (5 s to stabilization) compared to longer durations in subsequent trials (9–10 s), consistent stabilized speeds (14.62–14.98 km/h) but increasing space requirements for stabilization (13.49 to 31.70 m), and clear performance deterioration evidenced by decreasing maximum speeds (18.58 to 17.30 km/h) and minimum speeds (11.17 to 10.17 km/h). The marked differences in acceleration efficiency, quantified through slope analysis (2.58% to 0.74%), provided novel insights into technique deterioration across trials.

These findings have several practical applications for coaches and athletes. The real-time analysis of acceleration profiles enables immediate feedback on technique efficiency, while the quantification of the space required for stabilization offers a new metric for assessing training adaptations. The comprehensive analysis of velocity maintenance through maximum and minimum speed tracking provides objective measures for evaluating technical consistency and fatigue resistance. This technological approach has the potential to enhance canoe training methodology by providing coaches and athletes with objective data to support performance optimization and training periodization. It can be implemented post-training and, in the future, could allow real-time monitoring through on-device algorithm integration.

Author Contributions: Conceptualization, S.A. and S.B.; methodology, S.A., S.B. and C.D.G.-C.; software, S.A. and S.B.; validation, C.D.G.-C., M.G.-L. and J.P.-O.; formal analysis, S.A., S.B. and C.D.G.-C.; investigation, C.D.G.-C. and M.G.-L.; resources, J.P.-O. and M.G.-L.; data curation, C.D.G.-C.; writing—original draft preparation, S.A. and S.B.; writing—review and editing, C.D.G.-C., M.G.-L. and J.P.-O.; visualization, S.A. and C.D.G.-C.; supervision, M.G.-L. and J.P.-O.; project administration, J.P.-O.; funding acquisition, J.P.-O. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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Appendix A. The Steps That We Propose for Our Own Algorithm Are the Following

Step 1: smoothing the signal considering means in subintervals.

```
for i=1:n
mean(i)=classicalmean(series,x(i),x(i+1));
end
```

Step 2: define the cruising speed as the mean of the first speed, where the smoothed signal decreases, and the two consecutive means.

```
for i=1:n-1
    if mean(i+1)<mean(i)
        p1=x(i);
        ii=i;
        m=(mean(i+2)+mean(i+1)+mean(i))/3;
        break;
    end
end
  cruisingspeed=m;
```

Step 3: compute the local maximum and minimum.

```
 for i=ii+3:n-1
```

```
if mean(i)<min(mean(i-1),mean(i+1))
        minimo(i)=mean(i);
    end
    if mean(i)>max(mean(i-1),mean(i+1))
        maximo(i)=mean(i);
    end
end
```

Step 4: compute the range as the interval between the absolute maximum and the absolute minimum.

Step 5: Construct the best fit polynomial (in a least-squares sense) for the data in the interval [0, ts], where ts is the time where the speed is stabilized (Step 2). Compute the average of the slope of the polynomial.

```
for i=1:p1
    xx(i)=i/(lon(1)/(b-a));
    yy(i)=series(i);
end
tiempo=xx(p1);
pol=polyfit(xx,yy,s);

if s==1
    slope=pol(1);
    spacepol=pol(1) ×xx(p1)ˆ2/2+pol(2) ×xx(p1);
else
    slope=2×pol(1) ×xx(floor(p1/2))+pol(2);
    spacepol=pol(1) ×xx(p1)ˆ3/3+pol(2) ×xx(p1)ˆ2/2+pol(3) ×xx(p1);
end
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