Robust Real-Time Weightlifting Barbell Tracking in Diverse Scenarios: An Efficient Asymmetric Full-Search Algorithm based on Motion Vector Distribution

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Abstract: - An efficient algorithm for tracking weightlifting barbells in video sequences is presented in this paper. The objective is to rapidly and accurately extract the barbell's trajectory from weightlifting competition footage to support training and performance analysis. To accomplish this, a motion vector distribution-based asymmetric full-search algorithm is employed to identify regions with the highest similarity, facilitating precise object localization. Experimental results demonstrate that the proposed algorithm achieves accurate and stable barbell tracking in real time. This system provides athletes, coaches, and biomechanics researchers with an effective tool to analyze weightlifting performance efficiently and reliably.

Key-Words: - Computer-Aided Sport Training, Computer Vision, Object Tracking, Weightlifting.

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1 Introduction

Weightlifting holds a crucial position within the Olympic Games owing to its demonstration of peak human strength, precise technique, and the capacity for athletes to push the boundaries of physiological performance, [1]. For Taiwan, the academic and social significance of weightlifting is magnified by its role as a medium for national achievement and pride, exemplified by consistent international success. Most notably, Taiwanese athlete Kuo Hsing-chun achieved a gold medal in the women's 59kg category at the Tokyo Olympics, setting new Olympic records in both snatch (103kg), clean and jerk (133kg), and total combined weight (236kg). Furthermore, at the 2024 Paris Olympics, Kuo continued Taiwan's legacy by winning a bronze medal in the women's 59kg category with a combined total of 235kg, making her the first Taiwanese athlete to reach the podium in three consecutive Olympic Games. These achievements position weightlifting as more than a competitive discipline; it symbolizes Taiwan's resilience and capacity for global excellence and provides an inspirational role model for youth in sports participation and development. This dual importance—both as a key Olympic sport and a field where Taiwan excels—supports a strong case for further academic and practical investment in weightlifting.

Weightlifting coaches frequently employ mirrors within the training environment to facilitate real-time feedback on athletes' movement accuracy. The immediate visual response provided by mirrors enables athletes to self-assess the correctness of their technique. However, the transient nature of visual feedback may limit athletes' ability to retain proper form after the training session, thereby reducing the overall efficacy of skill acquisition. To address this limitation, video recording devices such as camcorders are also utilized. Both mirrors and camcorders serve as auxiliary tools that support athletes in observing and refining their performance. Nevertheless, the effectiveness of these methods is contingent upon the coaches' expertise and their ability to identify subtle variations in movement patterns; insufficient experience or methodological rigor may impede the accurate assessment of technical improvement or the detection of physical fatigue, [2].

Kinematic analysis is a foundational approach within sports biomechanics, extensively examined for its role in the quantitative assessment of athletic performance. Specialized kinematic analysis software enables precise measurement of key parameters such as motion trajectory and velocity, thereby facilitating deeper insight for coaches, athletes, and researchers into technical execution and skill proficiency. Despite its analytical power, the operational complexity and substantial time investment required by advanced analytical platforms may present barriers to adoption in applied sports settings. Conversely, digital sport video recordings serve as an accessible and highly practical resource, providing nuanced information critical not only for training optimization but also for competitive analysis. Video-based feedback supports both direct performance evaluation and strategic intelligence gathering, allowing coaches and athletes to reconstruct opponents' tactics and adapt preparation strategies accordingly, thereby advancing competitive advantage.

Kinovea, [3], is a widely used, open-source 2D motion analysis platform that offers measurable validity and reliability for certain kinematic parameters in sports and clinical contexts. However, the software faces notable limitations in professional use. First, Kinovea depends on substantial manual intervention for calibration and tracking, making the analysis process labor-intensive and time-consuming, especially for long videos or multi-joint movements. This reliance on user input can introduce subjective bias and inconsistencies across different raters. The software is limited to 2D analysis, which restricts its suitability for complex motions involving out-of-plane movement or depth, and decreases its accuracy relative to high-end 3D systems. In addition, achieving optimal measurement precision requires careful camera placement, high-quality video, and appropriate calibration, with accuracy decreasing as conditions deviate from these standards. These features make Kinovea suitable for basic and accessible motion analysis, but less appropriate for more advanced research or time-sensitive practical applications that demand automation, multi-dimensional analysis, and high throughput.

Video analysis constitutes a significant research area in computer vision, particularly in the domains of sports performance assessment and tactical evaluation. Conventional kinematic analysis systems frequently utilize 3D opto-reflective marker technology, which demands considerable expertise for precise marker placement on the body. These markers facilitate the generation of highly accurate human body models and the detailed tracking of limb movement. However, extensive time and resources are required to establish and calibrate the experimental environment. Additionally, many kinematic systems rely on infrared technology, rendering them unsuitable for outdoor applications where ambient light may interfere with recording accuracy. Despite the potential for high-precision motion capture, such methodological constraints—including the restrictive nature of marker attachment and reduced freedom of movement—limit the broader adoption and practical utility of computer-aided sport training and may negatively impact training performance by inhibiting natural movement patterns.

Trajectory serves as a critical parameter within kinematic analysis, providing meaningful insights for assessing the efficacy of athletic training interventions. Recent research, [4], [5], has highlighted a growing interest in quantifying barbell motion, with studies employing instrumentation such as triaxial accelerometers to capture barbell trajectories during lifting tasks. While sensors offer precise kinematic data, their practical application in the field is limited. For instance, following load release, the barbell may exert forces approaching 170.1G, [2], which can compromise measurement accuracy and potentially damage sensitive sensor equipment. Consequently, although sensor-based systems yield high-accuracy trajectory data in controlled environments, their suitability for data acquisition during actual competitions is constrained, precluding the collection of authentic in-competition athlete movement data.

In light of these limitations, video-based trajectory analysis emerges as a promising alternative for capturing barbell movement patterns in both training and competitive contexts. Video analysis circumvents the operational and equipment-related drawbacks of sensor-based methods and is broadly applicable to day-to-day weightlifting scenarios. However, conventional video kinematic analysis platforms are often hampered by resource-intensive operation. To address these challenges, this work aims to develop a robust, markerless barbell tracking algorithm capable of efficiently extracting precise trajectory data from weightlifting video sequences without reliance on external markers or sensors.

In this study, dynamic characteristics of the barbell during motion are explicitly incorporated into the algorithmic design. The classical diamond search algorithm, [6], [7], is systematically adapted and enhanced to facilitate the robust detection and tracking of the target barbell within video sequences. Specifically, pixel intensities within the identified barbell region are extracted as feature vectors and utilized for template matching across subsequent frames, employing an optimized diamond search pattern for efficient trajectory localization. Empirical validation is conducted using video datasets recorded at the 2017 Taipei Summer Universiade, serving as the benchmark for performance assessment. Detailed descriptions of the proposed algorithm and the corresponding experimental results are presented in subsequent sections.

The structure of this paper is as follows. Section 2 provides a comprehensive review of related literature. Section 3 details the development and theoretical framework of the proposed asymmetric full-search algorithm. In Section 4, experimental methodologies and results are systematically presented, while Section 5 concludes the paper with a synthesis of key findings and implications.

2 Relevant Works

Contemporary weightlifting biomechanical research emphasizes that Olympic weightlifting athletes require a sophisticated integration of technical precision, explosive power generation, and exceptional mobility to achieve optimal performance. The weightlifting movement constitutes a complex, continuous neuromuscular coordination sequence wherein the athlete accelerates the barbell from the platform to an overhead position through coordinated lower and upper extremity actions. Recent kinematic analyses demonstrate that successful snatch executions typically occur within a temporal window of 2-5 seconds, with elite performers exhibiting distinctive movement characteristics, including smaller knee joint angles during initial pulling phases (35.82%–78.45% of the movement cycle) and superior center of gravity control throughout the lift sequence. Contemporary seven-phase biomechanical models have replaced earlier simplified analyses, encompassing starter setup, first pull, knee crossing, full extension, transformation phases, bar clearance, and final fixation phases, [8], [9], [10], [11], [12], [13], [14].

Given the rapid temporal demands of competitive weightlifting, modern technological applications emphasize real-time performance feedback systems that can deliver kinematic analysis within optimal timeframes for coaching interventions. Recent studies demonstrate that real-time quantitative feedback significantly enhances both maximal strength (9.76% improvement) and explosive power parameters (31.30% improvement at higher loads) compared to conventional training methods. Advanced motion capture technologies and machine learning approaches, including LSTM neural networks, now achieve 71% accuracy in performance classification while processing barbell trajectory data in competition-relevant timeframes. According to the current International Weightlifting Federation Technical and Competition Rules and Regulations (2024), biomechanical analysis systems must provide actionable feedback within 90 seconds to satisfy practical application requirements for training and competitive analysis, [15], [16], [17].

Barbell kinematic parameters serve as fundamental observational tools for evaluating sport performance in contemporary weightlifting research, with particular emphasis on trajectory analysis, velocity profiling, acceleration patterns, and joint angle coordination, [14], [18]. Contemporary biomechanical analyses have established that barbell trajectory deviations, particularly horizontal displacement from the vertical axis, constitute critical determinants of lift success, [19], [20]. Research indicates that when trajectory deviation at the vertical axis becomes excessive, the barbell enters an unstable state that compromises lifting fluency and often results in failed attempts, [21].

Advanced sensor technologies, including inertial measurement units (IMUs) containing accelerometers, gyroscopes, and magnetometers, have emerged as sophisticated methods for capturing three-dimensional barbell movement characteristics, [22]. However, recent investigations, [23], highlight significant limitations of sensor-based approaches in competitive weightlifting environments. Critical concerns include sensor misalignment due to barbell rotation during lifting sequences, potential equipment damage from high-impact forces (documented barbell drop forces reaching 170.1G), [2], and psychological impacts on athletes during competition. Furthermore, sensor placement directly on barbells introduces measurement artifacts and is prohibited in official competition settings according to current International Weightlifting Federation regulations.

Recent advancements in video-based systems have significantly enhanced the measurement and analysis of barbell motion. For instance, [24] developed an unattended, video-based instrument for automatic measurement of barbell velocity during exercises such as the back squat, utilizing custom image-processing algorithms that track both barbell markers and multipower machine reference points through homography transformation and color segmentation. Traditional kernel-based tracking approaches, such as those relying on color histograms or illumination change, are sensitive to lighting variation—a factor known to decrease recognition and tracking accuracy. Algorithms like the five-degree-of-freedom color-histogram-based non-rigid object tracking method, combined with mean-shift optimization, are susceptible to illumination changes; thus, robust feature extraction and motion estimation remain active areas of research, [25].

While generic low-level feature-based algorithms often require substantial computational resources for feature extraction and similarity matching, recent methods now circumvent the need for extensive pre-training or annotated samples. To address this, the proposed video tracking schemes integrate local feature acquisition directly from video frames, followed by efficient similarity assessment via fast motion estimation, thereby achieving reliable performance with reduced computational overhead.

3 Proposed Tracking Algorithm

This section presents the design and implementation of our novel, efficient weightlifting barbell tracking algorithm. The primary objective of this work is to develop a computer-aided weightlifting analysis system that achieves both high computational efficiency and exceptional tracking accuracy when measuring the trajectory of a weightlifting barbell during competitions or practice settings. To accomplish this, the proposed algorithm integrates advanced motion tracking techniques tailored for dynamic and periodic barbell movements and is specifically optimized to minimize processing latency without compromising detection precision. A detailed system block diagram illustrating the major computational modules and procedural steps, as well as an in-depth explanation of each algorithmic component and its role in the overall tracking process, is shown as follows.

3.1 System Block Diagram

Fig. 1 presents the system block diagram of the proposed algorithm. To enable broad applicability, this approach processes general RGB video sequences, allowing the user to utilize footage from training sessions, competitions, or online sources. In the initial frame, the user identifies the barbell as the sample region, which is then stored in a buffer for reference in subsequent frames. Beginning with the second frame, the sample region from the previous frame is tracked using the proposed asymmetric full-search algorithm to locate the region of highest similarity in the current frame. This region of maximum similarity is assumed to correspond to the target weightlifting barbell. The displacement of the barbell between frames is represented as a motion vector, comprising vertical and horizontal components. The sample region is subsequently updated according to the barbell's position in the current frame, and the motion vector is recorded.

Upon completion of the pattern search within each frame, the proposed algorithm evaluates whether the current frame constitutes the final frame in the sequence. If it is not the terminal frame, the sample region is updated, and the search process is iteratively performed on the subsequent frame. Conversely, if the current frame is identified as the last frame, the motion vectors accumulated across all frames are concatenated to reconstruct the barbell's continuous trajectory throughout the video sequence.

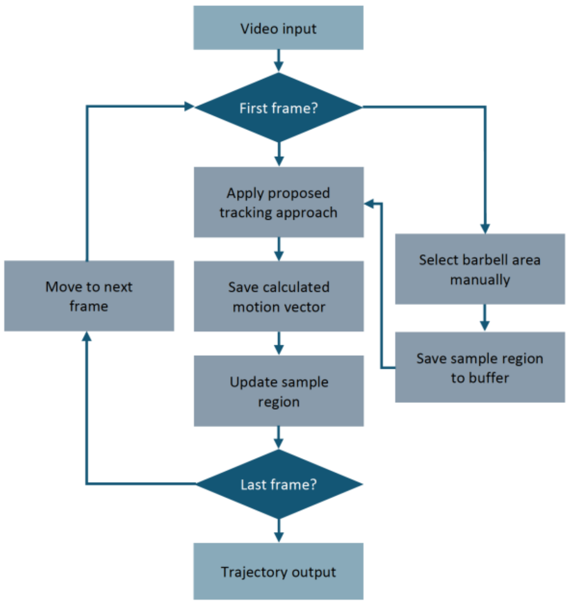


Fig. 1: System block diagram of proposed efficient weightlifting barbell tracking algorithm
Source: created by the authors

3.2 Proposed Asymmetric Full-Search Algorithm

Motion estimation and motion compensation are fundamental mechanisms in contemporary video coding systems, serving to mitigate temporal data redundancy and enhance compression efficiency. Most modern video codecs implement a block-based motion estimation framework, whereby each frame is partitioned into macroblocks of fixed dimensions ($m \times m$), and these macroblocks are utilized to assess the similarity between a current frame and its corresponding reference frame. Fig. 2 presents an illustrative example of the block-based motion estimation procedure.

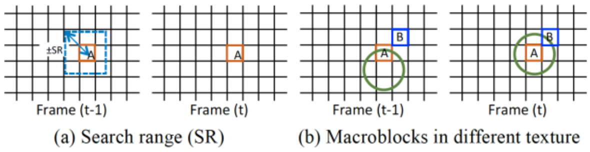


Fig. 2: Example of block-based motion estimation
Source: created by the authors

As shown in Fig. 2(a), a macroblock, denoted as A, is identified within the current frame, *Frame(t)*, with its spatially co-located position in the reference frame, *Frame(t−1)*. The motion estimation algorithm evaluates the similarity of macroblock A by comparing it with candidate macroblocks within a defined search range, $\pm SR$, surrounding the co-located reference position. The sum of absolute differences (SAD) metric, formulated in (1), is commonly employed to quantify the degree of similarity, providing computationally efficient object matching.

$$SAD_{(x,y)} = \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} \left| T_{(x+i,y+j)} - R_{(x+i,y+j)} \right| \quad (1)$$

where
m is the size of the macroblock,
x and y are the horizontal and vertical displacements,
i and j are the indices for pixels in the macroblock,
T is the pixel value in the macroblock in the target frame(t),
R is the pixel value in the macroblock in the reference frame(t-1).

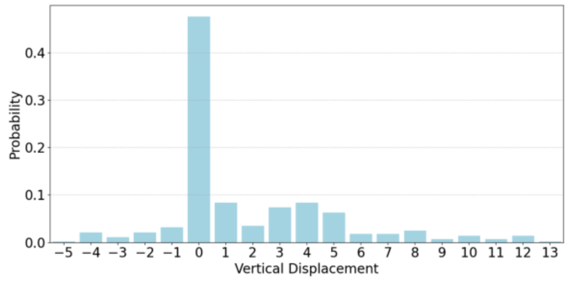
Nevertheless, practical scenarios often involve objects that span multiple macroblocks, as depicted in Fig. 2(b). In this case, macroblocks A and B in *Frame(t)* are both covered by the green circle representing the object, yet exhibit distinct texture characteristics. Notably, the corresponding macroblocks in *Frame(t−1)* may not be similarly covered, introducing inconsistency in motion vector assignment and potentially degrading tracking accuracy. Such limitations of the conventional block-based approach may lead to directional discrepancies when estimating motion vectors for contiguous regions of a single object. To address these challenges, we propose an object-based similarity comparison methodology, superseding the traditional block-based search scheme. Upon user-driven selection of the target barbell in the initial frame, the algorithm autonomously tracks the moving barbell throughout subsequent frames. Fig. 3 provides examples of barbell sampling as selected by the user in the first frame across multiple video sequences.

Fig. 3: Barbell areas sampled by the user from the first frame of video sequences
Source: created by the authors

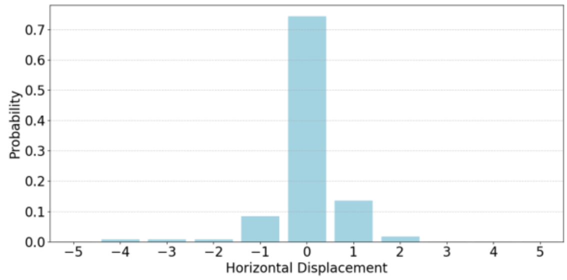
After selecting the target barbell, we apply our proposed asymmetric full-search algorithm to identify the region with the highest similarity in the subsequent frame. The full-search algorithm was originally introduced in [26] in 1981. They established the fundamental framework for motion estimation and proposed the full-search method, which involves a sliding window to examine all possible regions in the reference frame, ultimately identifying the block with the minimum error as the optimal match. This concept has directly influenced the development of motion compensation mechanisms in later standards, including MPEG, H.261, H.263, and H.264.

After conducting biomechanical analyses on over 100 weightlifting videos, distinct motion patterns of the barbell were identified, highlighting that it predominantly moves in the vertical direction and tends to approach the athlete throughout most of the lift. Based on these observations, our statistical results in Fig. 4 showed that the matched motion blocks frequently cluster within specific intervals in both the vertical direction (Fig. 4(a)) and horizontal direction (Fig. 4(b)), rather than being evenly distributed throughout.

This empirical evidence guided the development of our Asymmetric Full-Search Algorithm, which narrows the search region to *x[-1,2]* and *y[-4,12]* accordingly as depicted in Fig. 5. Unlike the traditional full-search algorithm, which exhaustively evaluates 289 candidate blocks via SAD (1) to ensure optimal matching accuracy, our algorithm strategically restricts computations to 68 candidates, exploiting knowledge from weightlifting biomechanics.



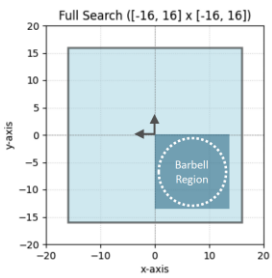
(a) Vertical distribution



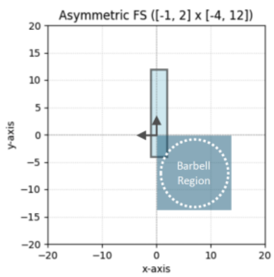
(a) Horizontal distribution

Fig. 4: Motion vector distribution
Source: created by the authors

This targeted approach enables a substantial reduction in computational burden—lowering the required SAD calculations by 77%—while experimental verification on our dataset shows that match accuracy remains at 100%, equaling the full-search benchmark. Not only does this improvement make real-time motion tracking feasible in sport biomechanics applications, but it also preserves the reliability and precision essential for athlete performance analysis and coaching feedback.



(a) Search range of FS



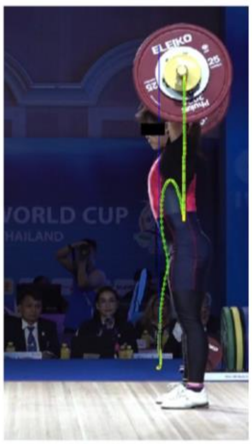
(b) Search range of asymmetric FS

Fig. 5: Proposed asymmetric full-search algorithm
Source: created by the authors

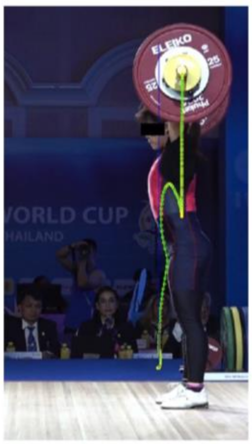
4 Experimental Results and Discussion

The experimental results are presented and analyzed in this section. Our test videos were captured during the 2019, 2022, and 2023 IWF world championships. All recordings were made using a consumer-grade digital video camcorder at full HD resolution (1920×1080, 60 frames per second) and encoded with the H.264 video codec. The proposed algorithm was implemented on a Windows 11 platform using the QT and OpenCV libraries, [27]. The development environment utilized an Intel Core i7 processor and 16GB of RAM. In addition to implementing the proposed asymmetric full-search algorithm, we also implemented the conventional full-search algorithm for comparison. For consistency across all video sequences, the sampled region for the barbell was set to 40×40 pixels, and the full-search range was set at ±16 pixels.

Fig. 6 presents the subjective quality comparison between the full-search and the proposed asymmetric full-search algorithm. The Fig. 6(a) and Figure 6(b) display the results produced by the full-search and proposed asymmetric full-search algorithm, respectively. The trajectory and position markers are rendered in real time. In Fig. 6, the green solid line represents the trajectory, illustrating the movement path of the barbell during lifting and lowering. Yellow circles indicate the projected barbell position at each frame onto the current frame. The trajectory and inter-marker distance enable users to assess and quantify the lifter's performance. It is evident from Fig. 6 that the trajectories in both Fig. 6(a) and Figure 6(b) are identical. Additionally, the position markers serve as visualization tools for analyzing sport performance. For instance, the distance between any two yellow circles can represent the duration of barbell movement between corresponding frames, allowing users to estimate the barbell's velocity during the lift.



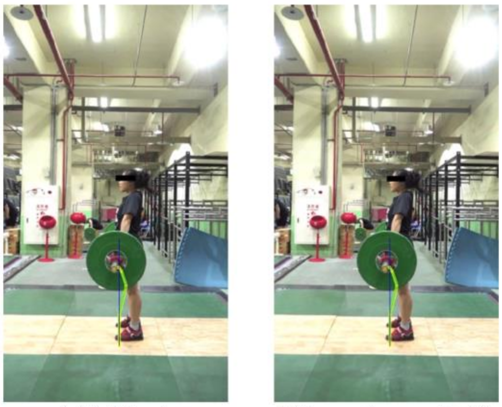
(a) Full-Search



(b) Proposed asymmetric FS

Fig. 6: Comparison of subjective quality between the full-search and the proposed asymmetric full-search algorithm
Source: created by the authors

Fig. 7 and Fig. 8 present experimental results under two different scenarios. Fig. 7 illustrates the outcome of the deadlift experiment, with Fig. 7(a) showing the results obtained using the full-search method and Fig. 7(b) depicting those obtained with our proposed algorithm. The visual similarity between these two subfigures demonstrates that our algorithm achieves comparable subjective performance to the conventional full-search approach in the context of deadlift motion. In contrast, Fig. 8 presents the results for the no-lift scenario. As shown in Fig. 8(a) and Fig. 8(b), even when the barbell trajectory deviates from the intended path, our algorithm still produces results equivalent to those of full-search. These findings confirm the robustness of our method across different motion patterns.



(a) Full-Search (b) Proposed asymmetric FS

Fig. 7: Comparison of deadlift between the full-search and the proposed asymmetric full-search algorithm
Source: created by the authors

(a) Full-Search (b) Proposed asymmetric FS

Fig. 8: Comparison of no-lift between the full-search and the proposed asymmetric full-search algorithm
Source: created by the authors

The experimental results on computational load indicate that our proposed Asymmetric Full-Search Algorithm achieves an average processing time of approximately 11.06 ms per frame, substantially lower than the conventional Full-Search Algorithm's average processing time of about 104.93 ms per frame. This demonstrates significant reductions in both computational complexity and processing time. In addition, the structure of our Asymmetric Full-Search Algorithm supports straightforward hardware implementation due to its regular data flow and reduced control overhead when compared to more complex or adaptive search strategies. Overall, this work presents a practical optimization for motion estimation in weightlifting video analysis, balancing computational efficiency and analytic robustness.

5 Conclusion

This paper introduces an efficient algorithm for tracking weightlifting barbells. By analyzing the motion vector distribution of the barbell, an asymmetric full-search algorithm is designed and implemented. The proposed approach significantly reduces computation time while maintaining robust tracking performance. To validate the quality and effectiveness of the algorithm, we employed general RGB videos captured during actual competitions at the 2019, 2022, and 2023 IWF World Championships. Compared with the conventional full-search method, the algorithm achieves equivalent tracking accuracy with substantially lower computational requirements. Furthermore, the algorithm facilitates rapid comparison of trajectories, allowing for the efficient analysis of movement patterns between different lifters or between multiple attempts. The comparison of trajectories for two lifters or two attempts can be completed in a short period of time. Notably, whereas traditional kinematic analysis software typically requires more than ten minutes for such analyses, the proposed asymmetric search algorithm enables computer-aided weightlifting training to be conducted with considerably greater ease and speed.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and verifies that none utilized artificial intelligence (AI) tools were used. The authors take full responsibility for the content of the publication.

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The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

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