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Biomechanical Analysis Using Motion Capture Suits and AI in Sport: A Data Science-Based Reflection

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Abstract:	Currently, the repetitive movement in different environments and types of sports training in some disciplines such as basketball, athletics, volleyball, and weightlifting; along with the management of techniques according to the kinematics of movement increases physical and mental health problems in athletes. Therefore, it is urgent to use technological tools to analyze the movements from data to prevent injuries. We propose the integration of motion capture suits supported by artificial intelligence (AI) for the collection and processing of biomechanical information based on real-time evidence to evaluate repetitive and permanent activities in both amateur and high-performance sports training. Applying the PRISMA methodology to review scientific literature between 2017 and 2024 in databases such as IEEE Xplore, Scopus and SpringerLink, with terms such as “motion capture suit”, “artificial intelligence” and “biomechanical analysis”, in addition to the authors' own methodology for the interpretation of contrasted data on postures, turns, angles, musculoskeletal specifically with the teslasuit 4.8, which uses IMU6 and 9-DOF sensors, using a time series of 3,169 samples with 273 variables. Finally, the emerging technologies articulated with artificial intelligence in sports, are definitive given the quantity, quality and validity of the data provided by motion capture suits; towards being able to find improvements in the very own technique of each athlete, optimize performance and mitigate injuries; Therefore, the evident benefits between the synergy between motion capture suits and artificial intelligence are reliable, adaptive according to the context and sport discipline to be analyzed, supported by data science, impacting positively, in the physical and mental health of high performance athletes.
Additional Information:	
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Biomechanical Analysis Using Emerging Technologies and AI in Sports: A Data Science-Based Reflection

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Abstract

Currently, repetitive movements in different environments and sports training in disciplines such as basketball, athletics, volleyball, and weightlifting, together with the use of techniques aligned with the kinematics of movement, increase physical and mental health problems. Therefore, it is necessary to use technological tools such as motion capture suits and spectral cameras that allow movements to be analyzed and converted into data and artificial intelligence models that can predict and prevent injuries. Their integration allows the collection and processing of biomechanical information to evaluate repetitive and permanent activities in both amateur and high-performance sports training. Applying their own methodology, the authors interpret the data contrasted in postures, turns, angles, and musculoskeletal aspects specifically with the Tesla Suit 4.8, which uses IMU6 and 9-DOF sensors, using a time series of 3,169 samples with 273 variables and a number of frames from spectral cameras to validate the level of confidence. These technologies, combined with artificial intelligence in sports, significantly reflect the quantity, quality, and validity of the data provided by these motion capture solutions, which allow for improvements in the athlete's technique, as well as improving performance and mitigating injuries. The obvious benefits of this synergy between technology and sports supported by artificial intelligence are highly reliable, adaptable to the context and sports discipline being analyzed, supported by data science, and positively impact the physical and mental health of athletes in different disciplines.

Keywords: Motion Capture Suits, Data Science, Biomechanical Analysis, Athletes, machine Learning, Quaternions, spectral cameras.

INTRODUCTION

Over the past decade, biomechanical aspects have gained relevance in the field of sports training due to their capacity to understand and optimize athletes' physical performance through precise study of human movement kinematics [1]. With emerging technology trends, such as motion capture suits, spectral cameras, and artificial intelligence (AI), a new approach has opened in the collection, processing, and analysis of data related to different types of sports activities, specifically in disciplines such as volleyball, athletics, baseball, basketball, and with scarce studies in weightlifting [2].

These emerging technologies provide sports training with more precise evaluation and enhance decision-making based on large volumes of information that, supported by artificial intelligence and data science, can improve sports practice with greater effectiveness and personalization, managing to mitigate risks and injuries during and after practice or training [3].

The integration of motion capture suits and spectral cameras articulated with artificial intelligence models is preponderant. These technological solutions, equipped with inertial, optical, or haptic sensors, allow real-time data capture associated with biomechanical variables such as velocity, acceleration, joint angles, and gait or movement patterns, among others, with the capacity to record human movement under natural conditions. Therefore, they provide fundamental information to be interpreted by machine learning models in a predictive or descriptive manner, enabling timely feedback in different training processes toward adaptive, quantifiable, and personalized experiences in the movements performed.

These technologies serving motion capture in sports activities [4]; facilitate automated analysis, pattern detection, and behavior prediction from high-quality data (over 95%), specifically with the Teslasuit, given the high fidelity of its sensors [5].

Motion capture in high-level sports training is strengthened by sensor miniaturization, suit portability, and the growing demand for biomechanical analysis, supported by spectral cameras with high precision levels through markers used outside the laboratory. Furthermore, artificial intelligence has rapidly evolved from simple predictive models toward complex algorithms such as deep neural networks and reinforcement learning, with the capacity to process multivariate and nonlinear data, being fundamental for modeling human behaviors in mobility environments that allow understanding, measuring, and optimizing them in different activities according to the sports application context [6].

Currently, technological advances and wearable solutions, articulated with sensor miniaturization, have allowed motion capture suits to evolve toward more affordable and scalable solutions, integrated with artificial intelligence tools applied to sports science [4, 24]. Despite these advances, the combined use of capture suits, high-precision cameras, and AI does not always respond to standardized frameworks nor has sufficient empirical validation to guarantee generalizable results [7]. Therefore, the present research attempts to define a machine learning model to predict physical behaviors.

Given all the above, it is fundamental to define a quaternion as a hypercomplex number with four components used to represent rotations and orientations in three-dimensional space, avoiding singularity problems associated with other representations such as rotation matrices. That is, it constitutes a way to represent a rotation through a vector of three elements (the direction of the rotation axis) and a scalar (the rotation angle) [8, 9].

This work focuses on analyzing information obtained from 6 and 9 degrees of freedom (DOF) IMU sensors of the Teslasuit 4.8 and from spectral camera sensors, to validate kinematic analysis of movement variable behavior that allows describing the three-dimensional spatial orientation of IMU sensors through mathematical representation of quaternions, both in the motion capture suit and in the spectral sensors of the cameras. This allowed integrating high-precision matrix models to capture movement data, including ergonomics and heterogeneous postures of athletes, facilitating the predictive artificial intelligence model to validate movement kinematics, present and future predictions and trends regarding athlete position, velocity, and acceleration, as well as early detection of possible specific events. Hence, the relevance of the study for fields such as biomedicine, health, sports, robotics, and autonomous systems, among others.

Finally, the divergences between technology and its articulation with sports are evident, presenting serious disagreements and currently lacking consensus on optimal parameters or variables for data collection, which hinders the creation of robust models for predicting athlete performance. This generates the research question: How is the integration of motion capture suits together with spectral cameras, supported by artificial intelligence, transforming biomechanical analysis and decision-making in sports training?

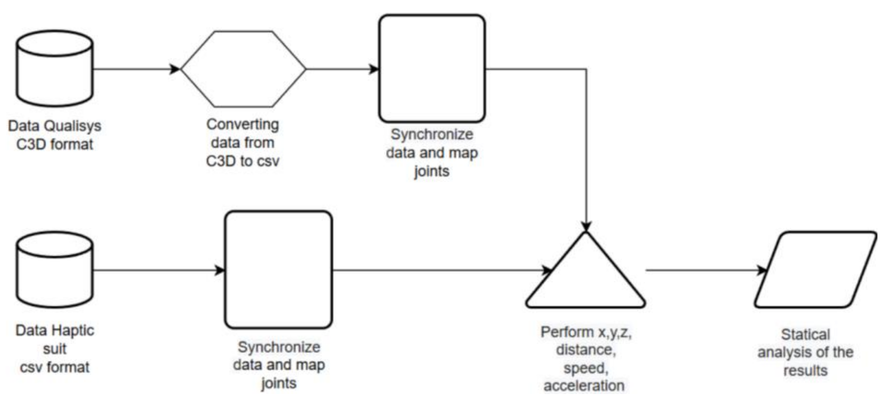
Therefore, the objective of this applied research is to analyze movement in different sports disciplines during their routine activities using the motion capture suit and high-definition cameras. The data provided by the sensors, with the help of an artificial intelligence model, will allow articulation as an integral set toward biomechanical analysis of the athlete, optimizing not only the activity performed but also predicting trends and postures that mitigate impacts and risks on both the physical and mental health of the athlete. The purpose is to identify trends, gaps, and future projections in this interdisciplinary field toward new research lines of academic and applied nature, with proven validity, conducting controlled laboratory tests with athletes who used the capture suit specifically in the weightlifting discipline.

METHODOLOGY

The methodology used to collect the data allows us to validate the accuracy of the information provided by the haptic suit against the reference data (Ground Truth) from the Qualisys M3 cameras during the tests. A cross-validation technique is applied, comparing the positions of key points of the skeleton (joints) captured by both systems. This technique is used to contrast differences between the measurements of each system for the same points at the same time, allowing us to determine their accuracy. Figure 1 shows the different phases proposed to determine the accuracy of the haptic suit data, using data from the Qualisys M3 cameras with 12 pointers.

Figure 1

Methodology to determine the accuracy of haptic suit data



Source: Own elaboration

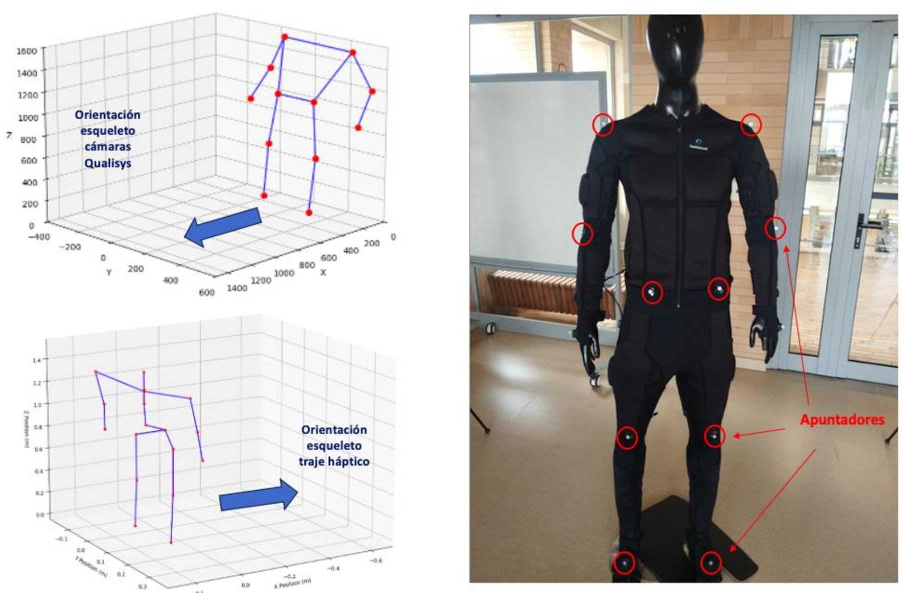
This proposal by the authors is based on a descriptive, correlational, and predictive pilot experimental study aimed at analyzing the dynamics of the quaternions obtained from the 14 IMU sensors integrated into the Teslasuit haptic suit[31]. This study aims to interpret the data provided by the suit in each test performed with the athletes. This study establishes a methodology that allows for standardizing the collection, processing, and analysis of the information generated by the haptic suit's sensors in a controlled environment, thereby establishing a solid methodological foundation before implementing more complex studies. Therefore, a phased analysis was applied as follows:

- Phase 1: Descriptive - Data Acquisition and Preparation.
- Phase 2: Data Extraction and Selection from the Haptic Suit.
- Phase 3: Kinematic Analysis

RESULTS

Figure 2 shows the arrangement of markers on the haptic suit corresponding to the 3 Qualisys M3 cameras used, locating the 12 markers on shoulders, arms, waist, and legs. Similarly, the skeletons generated for the haptic suit and camera joints are presented, synchronized as part of the Ground Truth exercise. Under this scenario, measurements were taken at 3 positions along the X-axis (0 m, 0.5 m, 1 m) with different athletes during the conducted tests.

Figure 2
Haptic suit skeleton models and cameras with synchronized data



Source: Own elaboration

Haptic suits are devices that provide tactile feedback to the user by simulating different types of sensations [10]. This Teslasuit 4.8 has a system capable of motion capture (MOCAP), haptic feedback, electrical muscle stimulation (EMS), and biometric data. It has 14 IMU sensors, operating in 6 or 9 DOF modes. The combination of sensors in each mode is crucial for the information it provides:

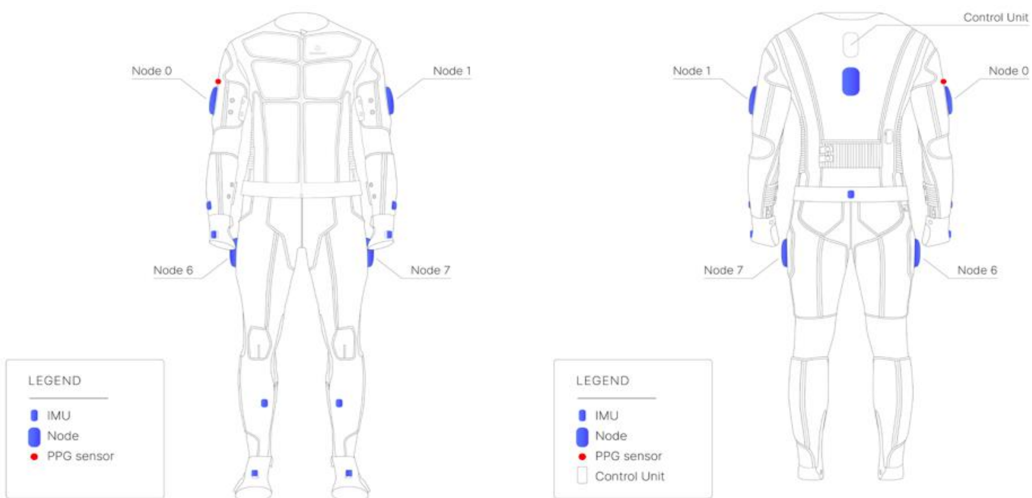
- The 9 DOF mode integrates data from an accelerometer (linear acceleration in x, y, z), a gyroscope (angular velocity in x, y, z), and a magnetometer (magnetic field in x, y, z). This combination is essential for providing comprehensive information about orientation and movement in three-dimensional space, including a global directional reference [27].
- The 6-DOF mode combines only data from the accelerometer and gyroscope [29, 30]. While it provides orientation and motion information, it lacks the ability to determine magnetic direction, which can affect long-term orientation accuracy without an external reference [31].

Figure 3 shows the location of the IMU sensors, nodes, photoplethysmography (PPG) sensor system, and the control unit. They are located as follows:

- Shoulder (left and right): 1 pair.
- Forearm (left and right): 1 pair.
- Hand (left and right): 1 pair.
- Back (jacket and pants): 1 pair.
- Thigh (left and right): 1 pair.
- Shin (left and right): 1 pair.
- Foot (left and right): 1 pair

Figure 3

Location of IMU sensors (front-back)



Source: [31].

Table 1 presents the specifications of the 14 IMU type sensors for motion capture.

Table 1

Technical specifications of IMU sensors

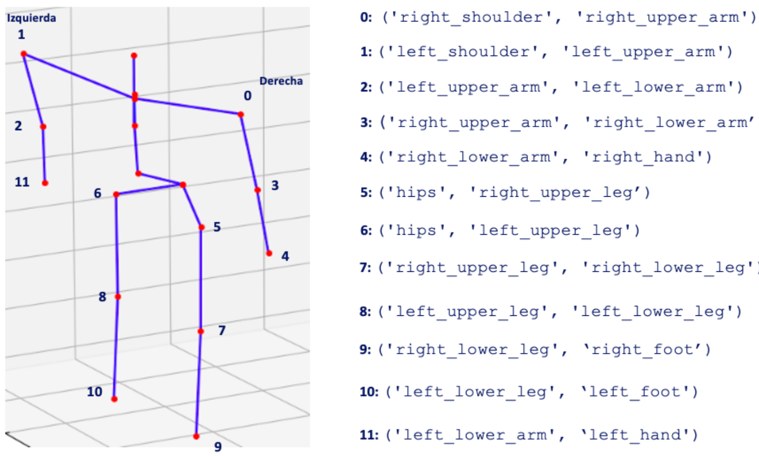
Motion Capture - MOCAP	
Number of elements	14
Type	IMU type 9 and 6 axis mode
Location	Integrated, fixed, anatomical
Frame rate	Up to 100 frames/sec.
Roll & Pitch	0,5º
Heading	1º

Source: Own elaboration with information taken from [31]

Among the technical characteristics of the haptic suit, its capacity to emulate tactile sensations in augmented reality environments stands out. For this purpose, the device integrates 114 electrodes distributed across 80 channels, which operate through electronic muscle stimulation (EMS) and transcutaneous electrical nerve stimulation (TENS) technologies. Additionally, the suit incorporates a photoplethysmography (PPG) system, a non-invasive technique that consists of emitting light toward biological tissue to subsequently measure the intensity of reflected or transmitted light, enabling the monitoring of physiological parameters [11, 26].

To perform distance measurements, both from the haptic suit data and from the Qualisys camera data, the data were synchronized and the joints were mapped, as shown in Figure 4 for the haptic suit.

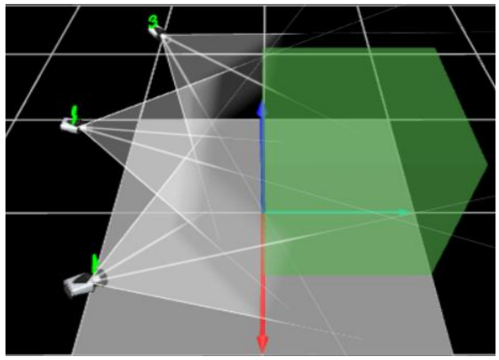
Figure 4
Skeleton joint mapping haptic suit



Source: Own elaboration

The spectral cameras used were the Qualisys Miqus, which allowed for adaptation and data acquisition in any sports discipline within an acceptable coverage range for motion capture on different types of bodies [25, 28]. This enabled the acquisition of high-precision and very low-latency data, using 3 cameras during the tests. The markers were strategically placed in the controlled tests (see figure 5). It was found that the camera speed is below 2-3 ms, and the system that integrates them is below 4-5 ms at distances of up to 10-20 m.

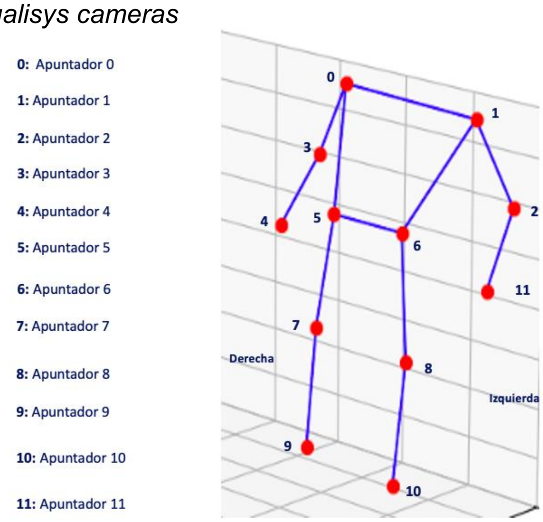
Figure 5
Testing and placement of cameras in athletes



Source: Technology solution provider https://www.qualisys.com/cameras/miqus/

Figure 6 shows the joints associated with the 12 pointers of the qualisys M3 cameras.

Figure 6
Skeleton joint mapping Qualisys cameras



Source: Own elaboration

During each of the proposed phases, data were collected as follows:

Phase 1: A dataframe in .csv format is obtained, generated from the Teslasuit tool environment [31], which displays information about the athlete's training each time they execute a weightlifting movement with different loads and specific test techniques, through 6 and 9 DOF IMU sensors during the activity.

During the test, dataframes containing 3,169 instances with 273 variables are obtained.
Table 2 shows the description of the dataframe variables, which present integer values for frame_number, frame_timestamp, left_foot, and right_foot (the latter two with dichotomous values: 1 for contact and 0 for no contact).

Table 2
Description of dataframe variables

Variables Names	Variable Description
frame_number	Frame number (sequential counter)

Variables Names	Variable Description
frame_timestamp	Frame time (ms)
root, hips, left_upper_leg, right_upper_leg, left_lower_leg, right_lower_leg, left_foot, right_foot, spine, upper_spine, neck, head, left_shoulder, right_shoulder, left_upper_arm, right_upper_arm, left_lower_arm, right_lower_arm, left_hand, right_hand	Each with position variables (.position.x, .position.y, .position.z) and rotation variables (.rotation.w, .rotation.x, .rotation.y, .rotation.z)
mass_center	With variables (x, y. z)
PelvisTilt, PelvisList, PelvisRotation, HipFlexExtR, HipAddAbdR, HipRotR, KneeFlexExtR, AnkleFlexExtR, AnkleProSupR, HipFlexExtL, HipAddAbdL, HipRotL, KneeFlexExtL, AnkleFlexExtL, AnkleProSupL, ElbowFlexExtR, ForearmProSupR, WristFlexExtR, WristDeviationR, ElbowFlexExtL, ForearmProSupL, WristFlexExtL, WristDeviationL, LumbarLatFlex, LumbarRot.angular, LumbarFlexExt, LowerThoraxLatFlex, LowerThoraxRot, LowerThoraxFlexExt, UpperThoraxLatFlex, UpperThoraxRot, UpperThoraxFlexExt, ScapulaDeprElevR, ScapulaProtrRetrR, ScapulaDeprElevL, ScapulaProtrRetrL, ShoulderAddAbdR, ShoulderRotR, ShoulderFlexExtR, ShoulderAddAbdL, ShoulderRotL, ShoulderFlexExtL	With angular variables angular, (.angle), angular speed (angular_v) and angular acceleration (angular_acc)
left_foot, right_foot	With variable state of contact with the ground (or with a surface)

Source: Own elaboration

During Phase 2. The collected data generates values for the vector position (x, y, z) and rotation (w, x, y, z), of the 20 variables indicated in Table 2. Therefore, a unit quaternion (w, x, y, z) represents a rotation, where w is the scalar (real) part and (x, y, z) are the vector (estimated) part. The Teslasuit tool [31] obtains the values of the rotation variable w, applying the fundamental relationship of unit quaternions [12] as follows:

$$w^2 + x^2 + y^2 + z^2 = 1$$

Clearing the equation, we obtain that:

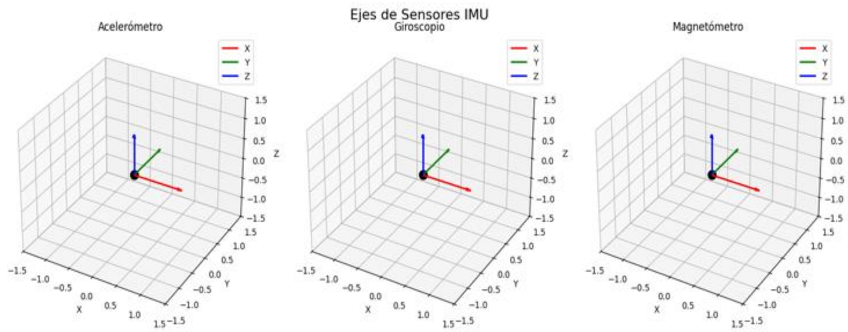
$$w = \pm\sqrt{1 - x^2 - y^2 - z^2}$$

Achieving an efficiency greater than 99%. The analysis of the quaternion calculation is performed intrinsically in the haptic suit's IMU sensor using the following process:

- Sensor fusion: Accelerometer (linear acceleration), Gyroscope (angular velocity), Magnetometer (magnetic field direction)
- Fusion algorithm: Madgwick, Mahony
- Quaternion calculation: Extended Kalman Filter (EKF), Complementary Filter, Madgwick AHRS algorithm

Figure 7 shows the static visualization of the accelerometer, gyroscope, and magnetometer within the three-dimensional environment, using the Python language.

Figure 7
Static display of 9_dof IMU sensor axes



Source: Own elaboration

The IMU located in the lower back/pelvis is used to estimate the values of the variables root.rotation.w, x, y, z. To estimate the position values root.position.x, y, z, the system uses information from different IMUs of the suit. Figure 8 shows the normalization values of the quaternion root.rotation, with an estimated error less than 0.0001%, indicating that the Teslasuit uses high-quality sensor fusion algorithms with a confidence percentage above 99% of the data validated during each test and with each athlete.

Figure 8

Root.rotation normalization validation

root.rotation.w	root.rotation.x	root.rotation.y	root.rotation.z	normalizacion
0.219544	0.007416	0.975505	0.011588	0.999999
0.219638	0.007466	0.975485	0.011522	1.000000
0.219503	0.007462	0.975514	0.011621	1.000000
0.219519	0.007457	0.975511	0.011623	1.000001
0.219719	0.007495	0.975465	0.011669	1.000001
0.219629	0.007449	0.975486	0.011626	1.000000
0.219610	0.007464	0.975490	0.011602	1.000000
0.219579	0.007439	0.975497	0.011600	0.999999
0.219579	0.007419	0.975497	0.011614	0.999999
0.219566	0.007419	0.975500	0.011630	1.000000

Source: Own elaboration

In phase 3 Kinematic analysis: In figure 9 you can identify the roll, pitch and yaw angles in degrees, corresponding to the quaternion root.rotation.

Figure 9

Root angles.rotation, roll, pitch, yaw

root.rotation.w	root.rotation.x	root.rotation.y	root.rotation.z	root.roll_deg	root.pitch_deg	root.yaw_deg
0.219544	0.007416	0.975505	0.011588	178.359930	25.350919	178.759975
0.219638	0.007466	0.975485	0.011522	178.366498	25.361939	178.755397
0.219503	0.007462	0.975514	0.011621	178.354660	25.345972	178.753469
0.219519	0.007457	0.975511	0.011623	178.354517	25.347842	178.753994
0.219719	0.007495	0.975465	0.011669	178.347325	25.371209	178.747517
0.219629	0.007449	0.975486	0.011626	178.354124	25.360776	178.754627
0.219610	0.007464	0.975490	0.011602	178.356717	25.358561	178.753486
0.219579	0.007439	0.975497	0.011600	178.357729	25.354970	178.756710
0.219579	0.007419	0.975497	0.011614	178.356553	25.354986	178.758795
0.219566	0.007419	0.975500	0.011630	178.354603	25.353432	178.758382

Source: Own elaboration

Below are the descriptive statistics for the quaternion components root.rotation and the equivalent Euler angles in degrees (root.roll_deg, root.pitch_deg, root.yaw_deg) as shown in Figure 10.

Figure 10
Quaternion statistics root.rotation

	root.rotation.w	root.rotation.x	root.rotation.y	root.rotation.z	root.roll_deg	root.pitch_deg	root.yaw_deg
count	3169.000000	3169.000000	3169.000000	3169.000000	3169.000000	3169.000000	3169.000000
mean	0.189708	0.166200	0.804172	-0.511399	-101.151099	29.055073	152.546470
std	0.030652	0.043865	0.059928	0.147378	60.275870	2.783557	85.143665
min	0.100485	0.005781	0.725241	-0.630626	-179.981409	14.316886	-179.997154
25%	0.175050	0.164513	0.766253	-0.586887	-114.394817	28.172580	173.624382
50%	0.185075	0.176975	0.794168	-0.549067	-111.201103	29.290835	175.244422
75%	0.201101	0.187627	0.811460	-0.529589	-104.981718	30.683421	176.473511
max	0.331496	0.251927	0.983397	0.020797	179.963564	35.460047	179.979849

Source: Own elaboration

Finally, the following important aspects can be highlighted:

- **w (scalar part):** Shows low variability, as it relates to the magnitude of rotation, suggesting minimal rotation in the conducted tests.
- **root.rotation.y:** Is the dominant component on average, suggesting that the dominant rotation axis of the movement aligns with the Y-axis.
- **Roll:** Shows high variability in lateral swaying or tilting.
- **Pitch:** Shows very low variability.
- **Yaw:** Displays the highest standard deviation, suggesting that the suit exhibits significant rotations around its Z-axis.

DISCUSSION

In the different sources consulted regarding the integration of motion capture suits, spectral cameras, and artificial intelligence in sports biomechanical analysis, the following aspects are disaggregated in Table 3 to facilitate their interpretation: the current state of research on MoCap, cameras, and AI in sports analysis; the best practices and technologies used; the gaps and relevant aspects; along with additional observations pertinent to the object of study.

Table 3

Research for sports training

Author(s)	Relevance	Observations
[1]Van der Kruk & Reijne (2018)	Review of motion capture systems; analysis of accuracy and applicability	Provides a basis for selecting appropriate systems according to specific sport needs.
[13] Mathis et al. (2020)	Principios y desafíos de la captura de movimiento con aprendizaje profundo.	Principles and challenges of motion capture with deep learning.
[14] Garrido-Lopez et al. (2024)	Development of VideoRun2D: a markerless motion capture system for sprint biomechanics.	Presents a cost-effective and accurate solution for sprint analysis without the need for physical markers.
[15] Hsu, Y.-H., Yu, C.-C., & Cheng, H.-Y. (2024)	Proposes a novel method for capturing shots in badminton matches from a monocular camera.	Uses the YOLOv7 model to identify if the player is hitting.
[6] Scataglini et al. (2024)	Comparison of motion capture systems with and without markers in gait analysis.	Provides critical insight into the accuracy and applicability of both approaches.
[16] Baumgartner & Klatt (2023)	Monocular 3D human pose estimation for sports broadcasting using partial sports field registration.	Addresses challenges in 3D pose estimation from 2D images in real-world sports environments.
[17] Ingwersen et al. (2023)	SportsPose: A dynamic 3D dataset of sports poses.	Presents a valuable resource for training and evaluating pose estimation models in sports.
[18] Canavan, P. K., Suderman, B., Yang, N (2021)	Baseball pitch analysis using a full-body motion capture suit.	Case study demonstrating applicability in sports performance analysis.
[7] Aderinola, T. B., et al. (2023)	Sports performance analysis enabled by computer vision.	Evaluating the feasibility of markerless motion capture using a single smartphone.
[19] Peng, X. B., et al. (2018)	Reinforcement learning of physical skills from videos.	Method that allows simulated characters to learn sports skills from videos, useful in training.
[20] Wang, C., Wei, X., Yang, A., & Zhang, H. (2022)	The application of data mining technology in the field of physical education, data handling increases rapidly.	Adapting physical education content and teaching methods, based on AI models such as decision trees, contributes to improving athletic performance.
[21] Li, Z., Wang, L., & Wu, X. (2025)	A series of methods to build a realistic virtual platform and achieve real-time interaction between athletes and the virtual environment.	Athletes participate in training, receive immediate feedback and personalized guidance, helping to improve results and the training experience.
[22] Banchero, L., & López, J. J. (2024)	Shows advances in jump measurement using audio technology and Artificial Intelligence (AI) techniques.	Deep neural network-based algorithm enables identification of key takeoff and landing events from sound recordings.

Author(s)	Relevance	Observations
[23] Garrido-Castro, et al.	Kinematically validate the volleyball spike technique using three-dimensional motion capture and analysis	Tool for training based on observed deficiencies and mitigating injuries in the medium/long term
[2] Pincay, R. D. M., & Godoy, A. L. M. (2024)	Understand the effects of how AI personalizes and adapts to sports exercise programs	The importance of addressing the challenges of effective technology implementation in sports
[5] Triviño, J. L. P. (2022)	Analyzes the advantages and disadvantages of AI by distinguishing various senses of sport	Establishes measures that distinguish the types of improvements in natural talents in sporting achievement.

Source: Own elaboration

CONCLUSIONS

The present research conducted in the sport discipline of weightlifting with athletes who used the haptic motion capture suit and spectral cameras with 3 installed units, containing high-precision sensors with fidelity and confidence above 99% and latency less than 2-3 ms, allowed finding relevant information during each test and training session with different athletes. These IMUs validate and capture acceleration data, angular velocity, and in specific cases, the magnetic field of a body, enabling identification of how a physical body is positioned three-dimensionally in X, Y, Z vector axes within a geospatial environment, validating postures, techniques, and movements that, supported by artificial intelligence models, improve and predict present and future trends in both performance and injury probability in athletes.

Both the Teslasuit haptic suit and spectral cameras enable descriptive and predictive analysis with the data, helping to identify variables for preprocessing and processing, considering the characteristics and biotypes of athletes, allowing validation of position techniques, angles, rotation (quaternions), and vector orientation in different axes and areas of athlete movement. It is relevant to highlight the high degree of reliability of the data obtained in the different tests performed, with an error percentage of 0.1%, showing excellent results, and with minimum latency of 2-3 ms. That is, these emerging technologies revolutionize high-level athlete training as the advantages of these technologies in service of sports become known.

These training support tools for athletes are preponderant for obtaining precise real-time data on kinematics in turns, angles, and postures in different types of sports movement, identifying patterns that help validate how technical or non-technical a movement can be in different sports disciplines, in addition to validating the level of precision that could not be perceived by the naked eye or through video. Their scalability, portability, and integration with textile technologies and Internet of Things (IoT) strengthen and optimize postures and repetitive movements in different sports disciplines.

The research highlights the importance of AI in extracting and analyzing data provided by the suits through machine learning algorithms, neural networks, and predictive models. These technological tools are capable of anticipating injuries, personalizing training plans, and optimizing individual performance. This has democratized access to precise biomechanical studies and increased data validity, highlighting how these solutions offer real-time feedback to coaches and athletes.

This type of technological tools used can be integrated into sports disciplines requiring high performance, identifying dysfunctional movement patterns before they become clinical injuries. In athletes, this reduces absenteeism and improves sports longevity. All these tools supported by AI with their trained predictive models are generating innovations in more effective training for health and physical performance.

Finally, challenges exist such as standardization of protocols in device placement on motion capture suits, use of spectral cameras, their interoperability between platforms, and the need for robust databases that allow processing the large amount of data generated by the suits to train AI models. The trend is evident: the integration of MoCap + cameras + AI systems is significantly transforming sports in the way human movement kinematics is measured, understood, and optimized. This synergy between sports and technology is promising, with solutions toward more personalized approaches according to sport, physique, weight, and height of the athlete, among other variables that can be contrasted, all scientifically grounded and with greater effectiveness.

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