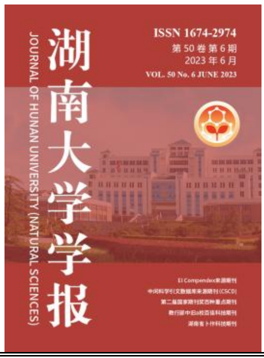

湖南大学学报（自然科学版）
Journal of Hunan University (Natural Sciences)

第 50 卷 第 6 期
2 0 2 3 年 6 月

Available online at http://jonuns.com/index.php/journal/index

Vol. 50 No. 6
June 2023

Open Access Article https://doi.org/10.55463/issn.1674-2974.50.6.11

Review of Optical and Inertial Technologies for Lower Body Motion Capture

Mauro Callejas-Cuervo*, Laura Alejandra Espitia-Mora, Manuel Andrés Vélez-Guerrero

Faculty of Engineering, Universidad Pedagógica y Tecnológica de Colombia, Tunja, Colombia

* Corresponding author: mauro.callejas@uptc.edu.co

Received: March 8, 2023 / Revised: April 5, 2023 / Accepted: May 2, 2023 / Published: June 30, 2023

Abstract: Motion capture systems play a vital role in diverse fields of knowledge, impacting multimedia content creation, sports, and assistive technologies in health sciences. This article offers an overview of human motion capture technologies with a focus on lower body analysis. Recent advancements are presented by compiling papers selected through the PRISMA method. The data were searched and extracted from various databases such as MDPI, IEEE Xplore, and Scopus, narrowing the observation window from 2018 to 2022, where 24 articles form the core of the review. The results indicate that 41% of the papers deal with technologies based on optical sensors, 24% with technologies based on MEMS sensors, 14% with technologies based on radar sensors, and 21% report the use of MEMS and optical sensor technologies. The technologies used were analyzed for their characteristics, motion information processing techniques, the type of results derived from each system, and their final applications. Based on this review, it is evident that there is a need to develop robust wearable systems that allow the fusion of different types of sensors to compensate for the weaknesses of each motion capture technology. In conclusion, the current state of motion capture technology emphasizes the development of health and rehabilitation applications.

Keywords: artificial vision, Doppler, gait analysis, inertial systems, microelectromechanical sensors, motion capture systems, optical systems.

下半身运动捕捉光学和惯性技术综述

摘要：动作捕捉系统在不同的知识领域发挥着至关重要的作用，影响着多媒体内容创作、体育和健康科学中的辅助技术。本文概述了人体动作捕捉技术，重点关注下半身分析。通过编译通过棱镜方法选择的论文来展示最新进展。从MDPI、IEEE探索和斯科普斯等各种数据库中检索和提取数据，将观察窗口缩小到2018年至2022年，其中24篇文章构成了综述的核心。结果表明，41%的论文涉及基于光学传感器的技术，24%涉及基于微机电系统传感器的技术，14%涉及基于雷达传感器的技术，21%报告了微机电系统和光学传感器技术的使用。分析了所使用的技术的特点、运动信息处理技术、每个系统得出的结果类型及其最终应用。根据本次审查，显然需要开发强大的可穿戴系统，允许融合不同类型的传感器，以弥补每种运动捕捉技术的弱点。总之，动作捕捉技术的现状强调健康和康复应用的发展。

关键词：人工视觉、多普勒、步态分析、惯性系统、微机电传感器、运动捕捉系统、光学系统。

1. Introduction

In recent years, there has been a steady increase in the number of scientific publications on human body motion capture systems. The reason for this phenomenon lies in the versatility of the captured data, which can be used in various applications, such as the development of diagnostic systems, in purely entertaining applications, such as motion generation for animation and video games, as well as in sports scenarios. In specific use cases, motion capture systems can be used to analyze the movement of the lower limbs using three currently predominant technologies: (i) inertial-magnetic sensors, (ii) sensors based on cameras and optical detectors, and (iii) Doppler-based detectors, each defining a set of parameters for acquisition and subsequent data processing [1].

In particular, the healthcare sector has embraced the use of motion capture systems in a variety of processes, as they enable the transfer of body movement information into a digital model that can be manipulated according to specific requirements. This digital versatility provides various analysis capabilities within and beyond the diagnostic and rehabilitation fields. In addition, this technology offers the ability to evaluate different parameters that detail a specific region of the body, i.e, it is possible to evaluate the lower and upper limbs or to obtain comprehensive information about the entire body.

With this in mind, regardless of the final technology used for motion capture, industry professionals can make an accurate diagnostic assessment. The measurement of motion parameters in the lower limbs alone is valid and reliable if limited primarily to high-end laboratories [2].

Collecting data in a controlled environment such as laboratory can improve the conditions of the collected data and thus increase the accuracy of the final information from the sensors. This is especially true for the previous example, where certain gait analysis processes involve determining the velocity of a moving torso [3] or analytically synchronizing multiple depth sensors to create a point cloud for tracking the foot surface [4]. Beyond this example, the specific use of motion capture systems based on optical or microelectromechanical sensors (MEMS) can capture a set of structured data belonging to the same context and identify a set of images using advanced computer vision techniques based on deep learning, which can be useful in health fields such as cardiology, pathology, dermatology or ophthalmology [5].

Looking at more specific use cases, it is easy to see a close relationship between new motion capture technologies and other sciences that, depending on their approach, adapt the various technologies currently available to solve increasingly difficult problems. Examples of this can be found in several private parties. For example, "Evolv Rehabilitation Technologies" has developed software that implements a physical rehabilitation system called virtual Rehab, which monitors movements through the use of video games with a commercial device originally designed for video game control (Microsoft Kinect for Xbox) [6]. However, using the same technology provided by Microsoft, it is possible to obtain a data set that automatically provides information on the performance of rehabilitation exercises, even in the absence of a physiotherapist and using simpler techniques [7].

Similarly, the advancement of depth cameras can support the development of user-specific protocols that allow individuals to perform target movements more effectively and accurately [8]. Because this type of technology is capable of capturing whole-body motion and is not limited to segments or areas, it can be used to improve an athlete’s performance [9], assess musculoskeletal kinematics, identify movement patterns in real time using deep learning algorithms [10], or even identify risk factors for future injury [11].

Other types of applications developed from motion capture data can also be explored, such as film production, video game production, and animated reconstruction of biomechanical systems, as one of the many functions is the creation of computer-generated imagery (CGI) characters and the assembly of tensor space from 3D skeletal joints [12]. Sensors and cameras that can assess the depth of an image include Microsoft Kinect for Xbox, Intel RealSense, StereoLabs, and Orbecc. They are of practical use in assessing many different aspects of body function and anatomy [13], as 3D data provide richer spatial and temporal information compared to traditional RGB video capture [14].

Although the data acquisition systems mentioned above are related to inertial or optical sensors, a different type of technology has been addressed that explores a new framework for human pose reconstruction by implementing radar sensors and, in general, deep learning techniques that allow the construction of a 3D image, which is a way to compensate for the shortcomings of conventional technologies currently used. For example, Intel’s RealSense sensors are a low-cost depth camera that simultaneously captures an RGB image and a depth image with missing information during data acquisition. The solution was found using a texture synthesis algorithm that segments the RGB image using an object-oriented multiscale method, which allows much of the missing information to be filled in [15].

Given the increasing number of sensors currently available to capture human body motion and the growing number of digital information processing techniques that enrich the process, there is a need for a review that organizes and details recent advances in the literature focused on the analysis of the human lower body. This review covers the open access literature published in MDPI, IEEE Xplore, and Scopus databases from 2017 to early 2022. It covers important topics such as the characteristics of the technologies mentioned in the reviewed literature, the techniques and types of analysis used for motion capture, and some applications that reflect the use of this technology.

2. Materials and Methods

In this review, the PRISMA method [17] will be used as a tool as it prevents biases in the documentation of the topic and enables a clear and transparent presentation of the systematic review of the selected literature. By following this process, the reader will gain a better understanding of the selection process in the different search sources on the topic addressed in this paper.

2.1. Eligibility Criteria

The eligibility criteria for literary material are: (i) material published between 2018 and 2022. A five-year window was chosen because of the notable increase and deepening of the subject matter covered in recent years; (ii) mainly English-language articles; (iii) open access articles; (iv) articles focusing on the use of artificial or computer vision, microelectromechanical systems (MEMS), motion processing units (MPU), or Doppler systems, and (v) articles with content related to human motion capture technology.

2.2. Search Methodology

Information was gathered from various research databases. The sources used for the literature search focused on Scopus, IEEE Xplore, and MDPI. A set of keywords was queried to explore the research topic, which was applied to the article title, abstract, and keywords fields. (The keywords included: “computer vision”; “artificial vision”; “motion detection”; “optical sensor”; “inertial sensor”; “radar sensor”; “technology”; “pose”; “human”. (ii) Words that could appear in the abstract were: “sports”; “health”; “leisure”; “entertainment”; “industry”. The specific search terms used in the different databases are shown in Table 1.

Table 1 Explicit query used to gather relevant papers in each database (The authors)

Database	Search Query
IEEE Xplore	((((“Full Text Only”: computer vision OR “Full Text Only”: artificial vision OR “Full Text Only”: machine learning OR “Full Text Only”: MPU OR “Full Text Only”: mems) AND (“Full Text Only”: motion capture) AND (“Full Text Only”: inertial sensor) AND (“Full Text Only): optical sensor)) OR (“Full Text Only”: radar sensor) AND (“Full Text Only”: doppler sensor) AND (“Full Text Only”: technology) AND (“Full Text Only”: human) AND (“Full Text Only”: pose) AND (“Abstract”: Sport OR (“Abstract”: Health OR (“Abstract”: recreation OR (“Abstract”: entertainment OR (“Abstract”: industrial)))); Filters Applied: 2017-2022; Open Access Only.
MDPI	“All fields”: computer vision OR “All fields”: artificial vision OR “All fields”: MPU OR “All fields”: mems AND "“All fields”: motion capture AND “All fields”: inertial sensor AND “All fields”: optical sensor OR “keywords”: radar sensor AND “All fields”: technology AND “All fields”: human AND “All fields”: pose; Open Access; Filter Years Between 2017-2022.
Scopus	((TITLE-ABS-KEY (computer vision) OR TITLE-ABS-KEY (artificial vision) OR TITLE-ABS-KEY (mems) OR TITLE-ABS-KEY(MPU)) AND PUBYEAR > 2016) AND (((((((motion capture)) AND (((inertial sensor) AND (optical sensor)) OR ((radar sensor) AND (Doppler))))) AND (technology)) AND (human)) AND (pose)) AND (Sport OR Health OR recreation OR entertainment OR industrial) AND (LIMIT-TO (OA, “all”)) AND (LIMIT-TO (LANGUAGE, “English”)).

2.3. Reduction by Manual Sorting

The application search queries used in the databases provide some documents eligible for this review. However, these documents are subject to a manual review that focuses on checking for compliance with the established criteria. A clear example of a document not being used is when the full text is inaccessible or there is no way to access the information contained in the database to find the document. Some documents are duplicated in the same or different databases.

Before the manual review, the total number of documents found by queries in the search stage was 68. As a result of the manual reduction stage, 2 documents with incomplete textual information were excluded, and 1 additional document was excluded for duplicates found in databases. Finally, 36 documents with no relevance to the subject matter of the audit were discarded.

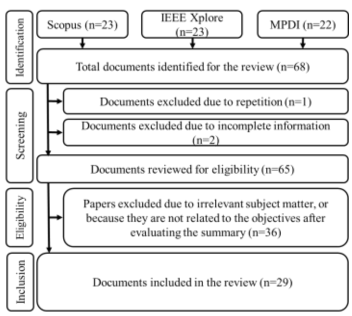

Fig. 1 A summary of the documentary selection for the review implementing the PRISMA methodology (The authors)

To better illustrate this selection process, Figure 1 shows a summary of the identification, screening, eligibility, and inclusion processes using the PRISMA methodology [16].

3. Results

The current section centers on the material derived from the bibliography selected and approved in the preceding documentary search. The findings are presented in a narrative format, where the content of each study is interpreted and analyzed. Table 2 furnishes a concise depiction of the 29 documents employed in this review. The table features the bibliographic reference of each document, its publication year, the database from which it was sourced, the technology utilized, the system's portability, the type of analysis carried out, and the final applications of the document.

Table 2 General characteristics of the reviewed literature (The authors)

Item	Ref.	Technology Type	Portability	Analysis Type	Applications
1	[17]	OPT	LP	Joint amplitude	Entertainment
2	[18]	OPT	N/A	Human activity	N/A
3	[19]	MEMS	HP	Cadence analysis	Sports
4	[20]	OPT +MEMS	LP	Human activity	Entertainment
5	[21]	OPT +MEMS	LP	Joint amplitude	Health & Rehabilitation
6	[22]	OPT +MEMS	LP	Gait analysis	Health & Rehabilitation
7	[23]	OPT +MEMS	NP	Human activity	N/A
8	[24]	OPT	NP	Gait analysis	Health & Rehabilitation
9	[25]	MEMS	NP	Gait analysis	N/A
10	[26]	MEMS	HP	Human activity	Health & Rehabilitation
11	[27]	OPT	N/A	Joint amplitude	Health & Rehabilitation
12	[28]	OPT +MEMS	LP	Human activity	N/A
13	[29]	OPT +MEMS	NP	Human activity	Health & Rehabilitation
14	[30]	MEMS	HP	Gait analysis	N/A
15	[31]	RAD	N/A	Human activity	Health & Rehabilitation
16	[32]	RAD	N/A	Cadence analysis Human activity	Health & Rehabilitation
17	[33]	OPT	N/A	Joint amplitude	Health & Rehabilitation
18	[34]	OPT	N/A	Joint amplitude	Health & Rehabilitation
19	[35]	OPT	NP	Human activity	N/A
20	[36]	OPT	N/A	Gait analysis Joint amplitude	Health & Rehabilitation
21	[37]	OPT	N/A	Joint amplitude	Sports
22	[38]	OPT	N/A	Gait analysis Joint amplitude Cadence analysis	N/A
23	[39]	OPT	HP	Joint amplitude	Sports
24	[40]	MEMS	N/A	Human activity	Sports
25	[41]	MEMS	HP	Human activity	N/A
26	[42]	MEMS	N/A	Human activity	N/A
27	[43]	RAD	N/A	Human activity	N/A
28	[44]	RAD	N/A	Human activity	N/A
29	[45]	OPT	N/A	Human activity	N/A

The following nomenclature is considered in Table 2. In the technology section, there are three categories: the use of microelectromechanical systems (MEMS) such as inertial systems, the use of optical systems (OPT), and the use of radar systems (RAD). In the Portability section, there are four categories: low portability (LP), high portability (HP), non-portable systems (NP), and unknown portability (N/A). In the Analysis Type section, there are four categories: Gait Analysis, Cadence Analysis, Joint Amplitude Analysis, and Human Activity, the latter being the collection of related topics such as sensor position or markers for data collection, human action study, positioning, and pose estimation.

Considering the information in Table 2, it was reported that 38% of the documents obtained came from the MDPI database, 17% from IEEE Xplore, and finally 45% from the Scopus database. Of the documents reviewed, 41% deal with topics related to technology based on optical systems, 24% deal with information related to systems based on inertial magnetic sensors or microelectromechanical systems (MEMS), the 21% of the documentation deals with a mixed topic where inertial magnetic systems or MEMS systems are discussed along with optical systems, and the remaining 14% of the documentation deals with radar sensors or systems based on Doppler detection. Finally, 34% of the documentation deals with portable systems, while 66% does not deal with portable systems (or this information is unknown).

The results obtained using PRISMA method show that optical systems are prevalent in the publications obtained from the Scopus and MDPI databases. Furthermore, the Scopus, IEEE Xplore, and MDPI databases all refer to inertial and microelectromechanical systems. However, only the IEEE Xplore and MDPI databases contain publications referring to both optical systems and MEMS. Doppler sensing systems, on the other hand, are mentioned only in the Scopus and IEEE Xplore databases.

Notably, no publications were identified in 2018, 2021, and early 2022. However, in 2019, the database made a significant contribution of 40% to the published documentation, representing the highest percentage provided by IEEE Xplore. It is noteworthy that the Scopus database was the primary source of most of the contributions in the publications identified for 2021 and early 2022, accounting for percentages of 83% and 67%, respectively. The MPDI database played a critical role in providing 47% of the documentation identified using the PRISMA method in 2018 and 2019. The distribution of these results is graphically presented in Figure 2.

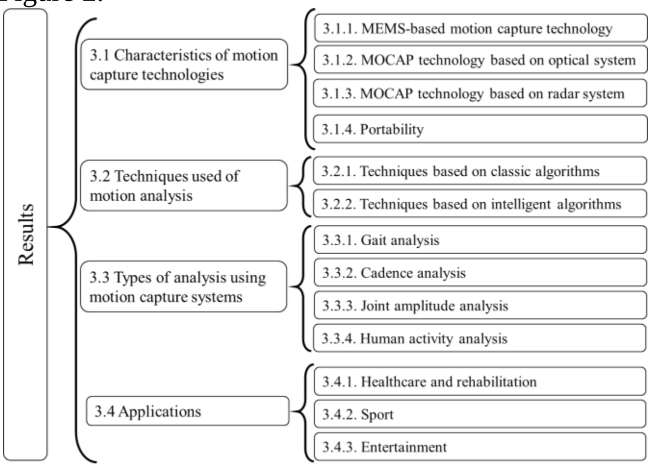

Fig. 2 Graphical structure of the elements addressed in this section (The authors)

3.1. Characteristics of Motion Capture Technologies

The mechanical movement of a human being requires the use of muscles, bones, and joint tissues. In this system, voluntary or skeletal muscles consciously control the movements of the human body by receiving electrical signals from the spinal cord and peripheral nerves due to commands from the cerebral motor cortex and cerebellum. This system is particularly interesting for research because it allows various studies to obtain information from the body, especially when noninvasive methods are required. Various instruments or technologies have been created to facilitate the acquisition of the necessary information, providing valuable assistance in the evaluation of neuromuscular behavior related to movement.

For motion monitoring, it is important to be aware of the different current technologies that are available for a variety of sensors, as discussed in [21]. These include fiber optic systems, optical goniometers, image and video-based tracking systems, textile sensors, gyroscopes, magnetometers, and inertial sensors, which make up the vast majority of commercially available joint and activity tracking devices.

Irrespective of the type of technology employed, miniaturization of all components is a common feature of motion capture systems. This attribute is necessary to prevent any interference with the object or subject under study movement. Moreover, the placement of the devices is a critical consideration as their initial positioning in the workspace (laboratory, measurement room, on the person, etc.) must be optimal to ensure the acquired data accuracy and avoid distortion. Furthermore, optical system technology necessitates motion detection sensors, algorithms, and parameterizations that vary depending on the specific use or final application, which may have more stringent requirements in clinical or medical scenarios [20].

A radial diagram summarizing the manufacturers of the measurement devices used in the reviewed studies is presented in Figure 3. The proprietary or research devices are the most prevalent, followed by XSens as the most popular company for MEMS systems, whereas Microsoft emerges as a significant player in the optical systems sector.

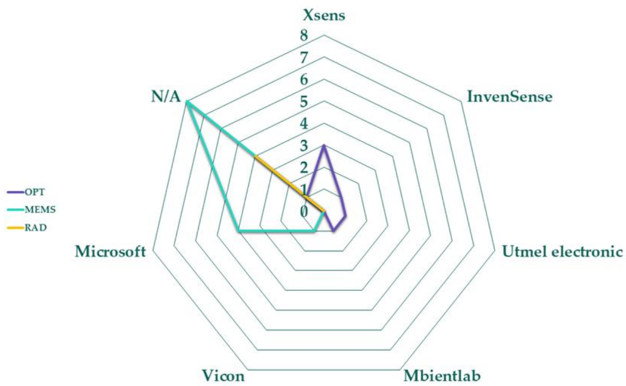

Fig. 3 Graphical representation of manufacturers developing motion capture technologies (The authors)

3.1.1. MEMS-Based Motion Capture Technology

Inertial measurement devices are available in various models and manufactured by different companies and their practical use is driven by their ability to provide highly accurate estimations on a short timescale through high sampling rates. Moreover, the technology is capable of capturing data on the position and orientation of the object or body segment being measured. However, an important limitation of these systems arises when the acquisition time extends to larger units, such as hours, leading to drifts in the integration or convergence of data.

Among the motion sensing technologies based on inertial magnetic units (IMU) with microelectromechanical systems (MEMS), there are a variety of devices, some of which are based on accelerometers, gyroscopes, magnetometers, or mixed systems. In general, accelerometers are used to measure vibrations or changes in the direction of the structure motion.

Gyroscopes measure the orientation of an object in space. Magnetometers measure magnetic fields, and finally, mixed or multichip systems have multiple circuits (ICs) in a single package, allowing them to be used as a single component capable of measuring accelerations, changes in orientation and changes in position relative to the magnetic field, and other variables in combination.

One solution to these drift problems is the integration of multiple sensors and models that enhance signal processing [42]. It is also worth noting that IMU systems offer several advantages, such as the possibility of measuring motion in real time and in environments where optical-based systems may face difficulties due to lighting and obstruction issues. However, IMU systems may have limitations in accurately capturing complex motion patterns that involve rapid changes in acceleration and direction, where optical-based systems may offer better performance.

Given the distinctive attributes of MEMS-based inertial measurement unit (IMU) systems and their extensive range of availability, they are used in numerous ongoing research studies to document human mechanical motion [23, 28]. Table 3 outlines a concise overview of papers that have incorporated inertial systems in their research, including the reference citation, sensor name, manufacturer, and various sensor characteristics that can be found in the datasheet.

Table 3 Characteristics of the inertial systems found in the documentation (The authors)

Item	Ref.	Sensor	Manufacturer	Characteristics
1	[19]	MVN	XSENS	• Technology based on miniature MEMS. • 3D human motion measurement systems. • Indoor and outdoor use. • Easy export to other software applications
2	[25]	MTi-1	XSENS	• 100 Hz sampling frequency
3	[22]	MPU6050	InvenSense	• Distributed angle detection. • IIC (Inter-Integrated Circuit) communication
4	[26]	BNO055	Utmel Electronics	• Provides fused absolute orientation data from an accelerometer, gyroscope, and magnetometer in the form of quaternions. • Configuration to operate in 9 degrees of freedom.
5	[29]	MetaSensor	Mbientlab	• High portable sensors. • Data collection from a 3-axis accelerometer, 3-axis gyroscope, and ambient light transducer
6	[30]	MARG	Unidentified	• Raw data are sent to a receiver via the Zig-Bee protocol at 100 Hz. • Use of accelerometer to correct gyroscope deflection • Use of a gyroscope to smooth accelerometer estimates
7	[41]	MTw	XSens	• Typical angular rate measurement range ±1200°/s. • Typical accelerometer range ±160 m/s2. • 50 Hz data sampling rate.

The ease of integration of MEMS-based technologies, the physical characteristics of IMU-MEMS, the low cost of some devices, the efficiency in detecting changes in the exercise of a movement in real time, the high accuracy, the different methods of processing the information obtained with this technology and the ability to provide signals that allow estimating the position and orientation of these systems were some of the features mentioned in the literature at the time of obtaining the results.

In addition, IMU systems can limit the detection of one or more positions according to their location on the body to be measured, which can lead to a cumulative position error if the positions are not aligned [23]. In addition, it has been reported in the literature that the position estimates and estimation of inertial sensors suffer from a deviation from integration on the time scale over long periods of use [42].

Similarly, some types of digital filtering to overcome the problems associated with drift are invalid for all movements in different human activities (e.g., when recording rapidly changing directional activities), where the individual accelerations per segment are more significant and long-lasting, and usually present additional magnetic disturbances [41]. Some of the limitations inherent in IMU-MEMS systems are not found in other types of motion capture technologies, giving way to systems based on optical technology, as presented below.

3.1.2. Motion Capture Technology Based on Optical Systems

In recent years, the use of optical systems for motion capture has become increasingly popular due to their noninvasive nature and ability to capture high-resolution data.

Various techniques and tools have been developed to capture and process data using this technology, including the use of reflective optical markers strategically placed on the subject or object to be tracked. These markers are easily detectable by sensors and help determine the position and trajectory of the subject in space.

Alternatively, there are markerless approaches to optical motion capture that rely on computationally robust processing methods. These markerless systems do not require external markers but instead use key points of one or more specific features of the object as a reference to determine or predict its position in an image. Marker-based systems, on the other hand, involve the use of external elements that are attached to the subject or object and whose position can be used as a reference in an image.

It should be noted that both marker-based and markerless systems have their advantages and limitations, and the choice of which system to use depends on the specific requirements of the application. For example, marker-based systems may provide higher accuracy and reliability but may be more invasive and cumbersome for the subject or object. Markerless systems, while less invasive, may be subjected to errors due to occlusion, lighting conditions, and other environmental factors.

Table 4 presents a succinct account of the literature on optical systems. Specifically, the table delineates the reference of the document, the type of sensor employed, the company that produces the sensor, whether markers are used for mechanical motion detection, and whether sensors are implemented for depth detection.

Table 4 Characteristics of the optical systems found in the documentation (The authors)

Item	Ref.	Sensor	Manufacturer	Marker-based	Depth Sensor	3D Analysis
1	[17]	Kinect v2	Microsoft	Yes	Yes	No
2	[18]	IR-D Sensor	Generic	Yes	Yes	Yes
3	[22]	RGB Sensor	Generic	Yes	No	No
4	[23]	RGB Sensor	Generic	Yes	No	Yes
5	[24]	Kinect v2	Microsoft	Yes	Yes	No
6	[28]	RGB-D	Generic	No	Yes	No
7	[27]	Kinect v2	Microsoft	No	Yes	No
8	[29]	LifeCam Cinema	Microsoft	No	No	No
9	[33]	RGB-D Sens.	Generic	No	Yes	No
10	[36]	RGB Sensor	Generic	No	No	Yes
11	[37]	Vicon	Vicon	No	No	Yes
12	[38]	RGB Sensor	Generic	Yes	No	No
13	[39]	RGB Sensor	Generic	No	Yes	No
14	[45]	Kinect for Xbox	Microsoft	No	Yes	No

Table 4 shows that 46% of optical systems use markers, which is the most common method used in the years after 2019 to date. In contrast, 54% of optical systems were found to operate without markers.

The use of marker-based optical systems as a baseline for lower limb localization has been identified from the literature. In addition, papers that cover 3D reconstruction based on the same optical acquisition systems as well as the implementation of depth sensors are discussed in separate sections.

The study presented in [18] uses concrete examples to demonstrate the use of the three aforementioned features, resulting in increased accuracy in motion detection through data fusion. In contrast, publications such as [17], [24] use optical systems based on markers and depth sensors, which account for 71% of the systems that do not include 3D reconstruction. Similarly, papers [22], [38] are among the 43% of reviewed studies that use only systems based on optical technology with markers.

Other reviewed studies, such as [36]-[37], perform only 3D reconstructions and are among the 66% of studies that use optical motion capture systems without markers and depth sensors. However, 53% of the works include some kind of sensor (integrated or external) for depth detection [27]-[28], [33], [39], [43].

Finally, [23] reports an implementation based on 3D reconstruction combined with the use of markers. The study by [29] is a unique case, as it is the only work that reports the use of an optical system without markers or depth sensors, and does not perform 3D reconstruction, focusing only on information processing models.

3.1.3. *Motion Capture Technology Based on Radar Systems*

Following a trend toward Doppler-based detection systems for human movement tracking, radar sensors are showing promise in various fields, including sports, entertainment, and health. Compared to other motion capture methods, such as optical and inertial, Doppler-based systems have advantages, including the ability to detect human movement through clothing and in low-light conditions.

In addition, these systems can capture data in real time, allowing for immediate feedback and analysis.

Following a comprehensive review of motion capture systems, it has been observed that Doppler detection and the use of radar sensors are emerging as promising techniques. In this regard, it is essential to explore the key attributes and future research directions highlighted in the relevant literature.

Table 5 Characteristics of the Doppler-based systems found in the publications (The authors)

Item	Ref. Year	Characteristics	Future work
1	[31] 2018	• Long-term monitoring. • System capable of capturing respiratory rate and human activity. • System implemented in controlled laboratory environment. • Use of the SVM classifier. • Possible use in medical care.	• Use of the system for multiple users. • The improved accuracy of activity reconstruction.
2	[32] 2019	• The improvement of the 2% position between magnetic sensors and	• Real-time implementation on hardware platforms

		radars. • Use of SVM and ANN classifiers. • Assisted living implementation.	while maintaining a precision regime.
3	[44] 2021	• 3D pose reconstruction using UWB MIMO radar and CNN 3D. • Position detection and pose a reconstruction of occluded objects. • External factors such as the movement of fans or the echo from air conditioners make it noisy. • Possible use in rescue and health activities.	• Increased pose reconstruction range. • Optimization of detection in more complex environments.
4	[43] 2021	• The conversion of human activity videos to realistic and synthetic Doppler radar data. • Reduced computational burden for human detection.	• Use of the system for multiple users. • Add or simulate a Doppler signal that handles moving background scenes for data generation.

The implementation of Doppler-based radar detection systems for multiple users remains a major challenge in the field, with approximately 50% of the literature on this topic citing it as an area for future research. Nevertheless, it is worth noting that these systems possess numerous features that can augment and enhance the data collected by inertial measurement units (IMUs) or optical systems.

For instance, radar sensors can measure the absolute velocity and position of objects, which is particularly useful in applications such as sports where high accuracy and precision are required. In addition, radar-based systems have the advantage of being able to detect motion through obstacles and walls, making them suitable for indoor applications. Finally, future research could focus on combining radar-based detection with other technologies such as computer vision or machine learning to further improve the accuracy and robustness of the captured data.

3.1.4. Portability

The portability of motion capture devices is a critical factor when collecting data in different environments, in different locations, and with different types of segments to track. The portability of one system or another may vary depending on the type of technology used and the technical specifications of each manufacturer. High portability can be very beneficial for studies in different environments, as it is always desirable to be able to move the motion capture equipment easily and quickly, and to minimize the requirements of specific work areas for testing.

For this reason, in Table 2 above, the portability of the motion capture technology used in the reviewed papers has been classified according to portability levels as follows: High portability (HP) systems are those that can be easily relocated without the need to add or remove infrastructure elements and those that are efficient in any environment.

Low portability (LP) systems are those that can be moved to other environments but require additional infrastructure changes. Non-portable (NP) systems are those that are generally installed in a fixed location and under controlled or very strict environmental conditions in terms of technical or ancillary infrastructure. Finally, systems classified as an unknown (N/A) are those where it is not specified whether the system is portable or not. A graphical summary of the type of portability implemented by the technology is shown in Figure 4.

The solar projection in Figure 4 shows that 80% of MEMS systems are typically highly portable (HP), while the remaining 20% are optical systems. Thirty-five percent of the publications [17], [19]-[22], [26], [28], [30], [39], [41] indicate the use of portable technology, but 48% of the literature reviewed [18], [27], [31]-[34], [36]-[38], [40], [42]-[45] do not indicate whether the system is portable. In contrast, non-portable systems mentioned in publications [23]-[25], [29], [35] represent a 17% share.

Fig. 4 The graphical representation of portability according to technology types (The authors)

On the other hand, optical systems represent 20% of the portable technology, in contrast to combined systems and MEMS systems, which have a similar percentage value of 40%; therefore, due to the compact size that MEMS systems have, it can be concluded that a large part of the portable applications in this review use this feature in addition to the fact that they can achieve a high sampling rate in real time.

One of the reasons why some documents were classified as non-portable was the use of systems in closed and controlled environments, since in many cases they required specific conditions for the measurement of parameters, also size and weight were considered, since they can affect the ease of transport.

3.2. Techniques Used for Motion Analysis

Due to the high demand for motion capture systems, users and developers of these technologies have adopted various techniques to interpret, understand, and analyze the captured data. Recently, due to the rise of artificial intelligence, many optical systems are based on techniques that incorporate intelligent motion analysis algorithms, as shown in Figure 5. However, some MEMS-based motion capture systems also use these types of algorithms, although an approach based on the development of classical algorithms is used for these types of systems.

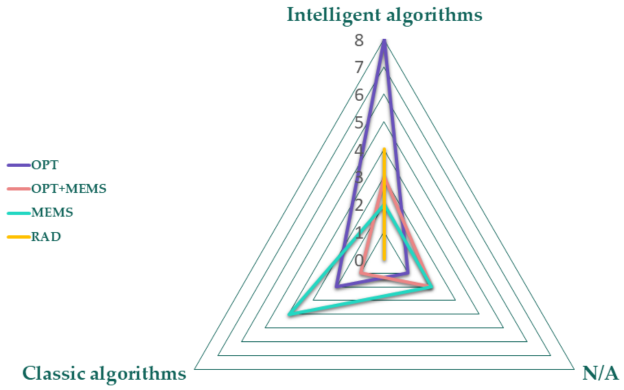

Fig. 5 Graphical summary of techniques used for motion analysis (The authors)

From the literature, it appears that it is not necessary to implement a specific type of algorithm, as the algorithms used should aim for higher efficiency of results depending on the type of application, regardless of the technology used. An illustrative example can be found in [30], where in addition to classical and intelligent algorithms, a combination of MEMS-based sensors is used for a preliminary evaluation of the rehabilitation of stroke victims with gait disorders. The various techniques discussed in the different documents studied are described below.

3.2.1. Techniques Based on Classic Algorithms

In the literature, there are several ways to process the information collected by these technologies. Various filters are often applied to the data collected by inertial sensors to optimize and improve the quality of the raw data obtained. An example implementation is the Kalman filter [22], [41]-[42], which provides noise reduction with a combination of triaxial acceleration and angular velocity by fusing values from different MEMS-based sensors [22].

Within this group of nonlinear filtering algorithms, there is also an extended version that allows accurate updating of the measurements in dynamic motion, as shown in [41]. Other works describe the use of a complementary Kalman filter [30], [42], whose main function besides information fusion is the suppression of computational errors, which finally finds application in the implementation of integral-proportional controllers [30]. Another filter different from those mentioned above is the FIR antialiasing used in optical systems, which allows the removal of frequencies higher than half the sampling frequency, a process that must be performed before data discretization [37].

Another way to optimize the collected information is to apply parameter optimization algorithms, which, depending on the application or purpose, may include Smoothing algorithms [25], [42] Robust algorithms [41], and Segmentation algorithms [24].

Smoothing algorithms directly evaluate the position, attitude, velocity, and acceleration of the target, and the resulting data can be compared through digital simulations of the results [25]. Another type of algorithm found that robust algorithms can be used for orientation tracking with large active accelerations, which are on average longer than the maximum sampling time of MEMS-based gyroscopes [41]. However, for three-dimensional trajectories, other algorithms such as segmentation algorithms can be used to capture the values of a joint without obtaining a high inaccuracy value [24]. For the concrete implementation of this type of algorithms and filtering techniques in various technical fields, versatile development platforms have been used, and the use of MATLAB [24], [37] and Arduino [22] is significant.

At the same time, it should be noted that the percentage of publications using classical algorithms to process the acquired signal is 33%. The tendency to use classical algorithms in MEMS systems is highlighted because they allow the manipulation of the information acquired by the systems and their final function is to optimize the quality of the acquired data by processing the information more efficiently. On the other hand, not all digital filters are suitable for different technologies, and in some cases, they are ineffective or counterproductive.

3.2.2. Techniques Based on Intelligent Algorithms

While the concept of an algorithm is based on the execution of actions according to a set of defined, ordered, and finite rules, the concept of intelligent algorithms does not follow defined rules, but is based on patterns that emerge from the analysis of various observable variables, as well as the incorporation of concepts or knowledge from other domains that provide a solution to a given problem.

There are currently notable advances in this type of processing and control techniques and their high use is evident in the papers that are part of this review. This category includes deep learning algorithms, which include several approaches based on data science and predictive models used by computer vision or machine vision [33]-[34], [36], [38].

Following this particular type of processing [17] describes the procedure of extraction and subsequent processing of images captured by a Kinect for Xbox camera and filtered by dimensionality reduction, which also combines principal components and Fisher’s discriminant analysis. In this work, a transformed feature vector extraction is created that finally feeds an input layer of an Extreme Learning Machine (ELMC) classification system based on Rectified Linear Units

(ReLU), providing efficient results that allow improving processing times without the need to implement weight learning, demonstrating better classification performances than conventional methods, e.g, K-Nearest Neighbor, Support Vector Machines (SVM) and Extreme Learning Machine (ELM).

Similarly, in [18], IR-D sensor data are acquired and processed to obtain correlated data pairs with depth views and multicolor optical flow. In this data processing architecture, each pair is fed into a fully convolutional network (FCN) model based on convolutional position machines (CPM), which outputs a 3D result of the executed pose. Other works such as [19] describe the realization of ensemble stacked auto-encoder (ESAE) algorithms, which are built from multiple stacked auto-encoders (SAE). These algorithms are neural networks composed of multiple auto-encoder (AE) layers complemented by a softmax function-based system that allows the reconstruction of data for the classification of horse stages based on MEMS technology for the acquisition of inertial and magnetic sensors.

On the other hand, the K-nearest neighbor algorithm is also widely used for human action recognition. Likewise, this algorithm has been used in researches such as [28-29, 43], although complementary to this one, there are other algorithms such as classifiers using Support Vector Machines (SVM), Random Forest (RF), Multi-Layer Perceptron (MLP) and Discrete Time Warping (DTW).

Similarly, the research presented in [39] applies a pose estimation algorithm to extract features from some movements, actively comparing four data mining algorithms (BayesNet, J48, MLP, and DeepLearning4j). As a result, it is found that these techniques can capture the predefined movements of Ippon Kihon Kumite (dataset specialized in karate movements) compared to other intelligent models, achieving an accuracy higher than 99%. However, the development has a postural diversity recognition system since the data are videos taken with a mobile camera while the karateka maintains a predetermined initial posture. This allows the recognition system to work with changing or dynamic values for areas that cannot be examined due to visual obstructions (occlusion).

In the study of further work in this review, complementary intelligent algorithms are found, such as the zero-velocity update algorithm [30], which was developed to solve the sensor derivation problem and eliminate computational errors. Finally, there are complementary approaches such as the algorithm based on the Tree-structured Parzen Estimator used to determine the values of the motion parameters [23].

As discussed in this section, there are several intelligent algorithms and adaptive information processing systems that simplify the cleaning and extraction of transactional data, allowing them to automate processes, reduce human errors, and speed up decision making. However, data are often missing and it is sometimes impossible to determine the reliability of the information. Developing and training these algorithms can be costly, so this technology is not widely available to researchers in various fields outside engineering.

3.3. The Types of Analysis Using Motion Capture Systems

The literature review that motivated this study shows that there are different types of analyses that can be derived from sensor data implemented with motion capture systems. Since information analysis includes not only the data collected by motion capture systems but also their digital processing and preparation, this section addresses a segmented approach to specific problems in the field of human lower limb assessment.

As a result, this study considers gait analysis, the analysis or determination of joint amplitude in different segments, human activity indicators, and cadence.

A summary of the different relationships between the type of analysis and the motion capture technology used can be seen in Figure 6. However, several types of analysis have also been observed in the same study or research, as in the case of [36], which performs a 3D reconstruction of the human body through association-based features, mining, and deep learning, resulting in an analysis of gait, joint amplitude, and cadence of different patients.

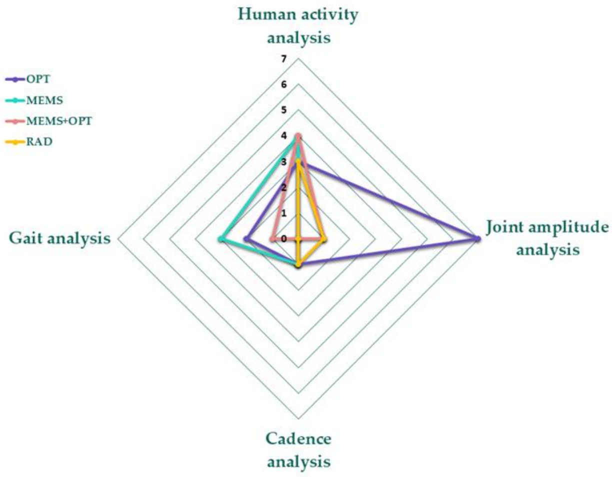

Fig. 6 Graphical summary of the analysis type (The authors)

3.3.1. Gait Analysis

The manifestation of a change in the values of a person's mechanical movements allows the identification of patterns used to detect multiple events. In the literature reviewed, several methods have been identified that use gait-specific analysis. One example is the research presented in [24], which investigates the ability of different systems to detect multiple gait characteristics in people who have suffered a stroke or have Parkinson's disease. The most important result was the determination of the degree of gait impairment. In another study, the rehabilitation of stroke patients was similarly assessed by observing the angular behavior of the foot, stride length, stride speed, and gait phase according to different gait rhythms [30].

In general, most studies aim to interfere as little as possible with the patient's natural gait pattern [36]. Beyond this aspect of not interfering with the natural behavior of the patient by the measurement systems, in [22] it is reported that by using cameras distributed in different areas of a course, the joint angle in the sagittal plane was considered for gait analysis with as little intervention as possible, while using this type of data to simulate an estimation of human walking motion [25]. More recent literature, such as that presented in [38], also describes the analysis of human posture to extract landmark information to obtain the 2D human skeletal network to reconstruct a 3D model that allows the detection of gait events with little or no impact on the patient's natural gait.

After these general provisions and the deepening of the information in Table 2, the segmentation by type of data analysis results in Figure 7, which shows the percentage value relating the technologies used in data acquisition to gait motion analysis.

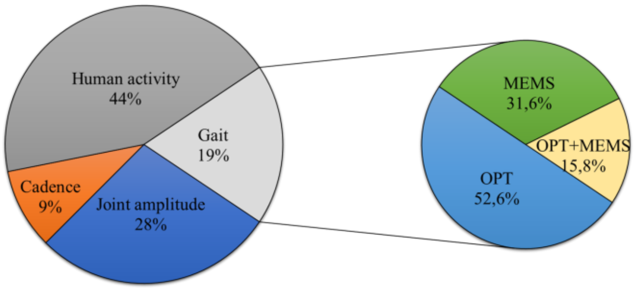

Fig. 7 Technologies implemented in gait analysis (The authors)

3.3.2. *Cadence Analysis*

Cadence analysis is a valuable metric that quantifies the regularity of repetitive motion over a specific period. This information can also provide useful insights beyond the study of human movement, as demonstrated by the parameters obtained from equestrian horseback riding. Additionally, cadence analysis has important applications in sports and artistic performances. Typically, this analysis considers values of hip and spine angles, which indicate the extent to which subjects correctly execute learned or trained movements [19].

Another critical analysis found in the literature is the three-dimensional reconstruction of the human body. This approach provides contextual features such as joint angles, degrees of freedom, and the direction of human motion flow, which can be extracted from the captured body parts [38]. Alternative methods for measuring these same characteristics are discussed in [32]. It is noteworthy that the technological approach employed for acquiring gait data and performing cadence analysis is presented in Figure 8.

Figure 8 shows that the percentage of publications using cadence-based applications is 9% of the literature, making this analysis the least common. In addition, MEMS-based inertial magnetic, radar, and optical systems can be used for analysis and data acquisition. As a result, this type of analysis makes it possible to evaluate the execution time of an event to determine the execution time of a posture or the repetition time of a sequence of actions. A clear disadvantage is seen in the analysis of cadence, since the system performing the data acquisition may be subject to interference depending on whether the measurement time is extended or not, as in the case of IMU-MEMS-based systems discussed earlier.

Future research could explore the integration of cadence analysis and three-dimensional reconstruction approaches to provide a more comprehensive understanding of human movement. These analyses could be complemented with other technologies, such as machine learning algorithms and artificial intelligence techniques, to enhance the accuracy and reliability of the captured data. Moreover, the application of these analyses could be extended to diverse fields, including rehabilitation and physical therapy, to provide objective measurements of patient progress.

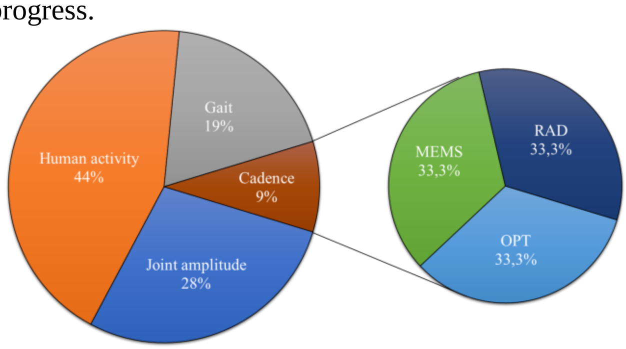

Fig. 8 Technologies implemented in cadence analysis (The authors)

3.3.3. *Joint Amplitude Analysis*

The analysis of the amplitude generated by a joint during an extension, flexion, and rotation movement can provide relevant values for the body's behavior, since these joints are often subjected to loads or overstretches when moving beyond the natural amplitude. One way to obtain angular trajectories is to implement intelligent and complex algorithms, such as a self-generating adversarial neural network (GAN model) [34]. Typically, these calculations are performed in complex processing systems such as OpenPose, which groups the anatomical positions of the body (called key points) into triplets that allow the angle between different parts of the body to be calculated [39]. This technique also allows data to be interpreted to understand degrees of freedom [38], momentum, force output, and power output when performing movements [37].

To understand and obtain information about joint amplitude, some work reports the use of markers that allow for more accurate identification of the participant's body size and its relationship to joint trajectory-based data [37]. This type of joint analysis is made possible by normalizing the information obtained from these markers. However, systems have also been implemented that do not require the use of markers and whose robust implementations allow distinguishing up to six central angles to characterize the movements of dancing [17] or to know the flexion of hips, ankles, or knees in other types of activities involving sport-specific movements [21], [36]. Figure 9 shows the percentage results of the technologies used to perform an analysis based on joint amplitude.

Figure 9 shows that joint amplitude accounts for 30% of the applications found in this review, with optical systems dominating over mixed OPT and MEMS systems. The main benefits cited in the literature include motion characterization, joint monitoring during daily and strenuous activities, and three-dimensional motion recording. In contrast, when analyzing joint amplitudes, only the angles (but not the times) at which the desired amplitude is reached are known.

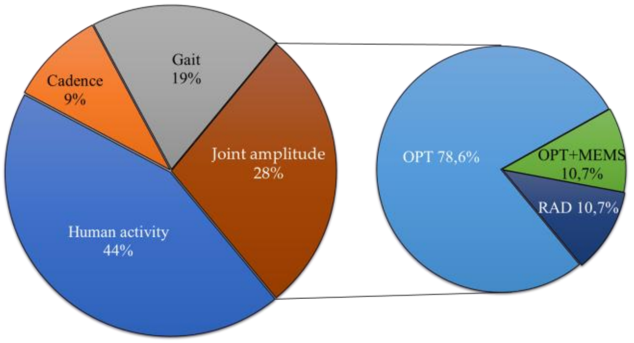

Fig. 9 Technologies implemented in joint amplitude analysis (The authors)

3.3.4. Human Activity Analysis

Human activity can be interpreted as intentional behavior that adapts to environmental stimuli and can be used in various domains. Nowadays, several methods and techniques allow to capture and collect this information. In this sense, the works presented in [20], [28], [35] use image processing systems that can locate the object of study and encode the movements with high precision.

Similarly, some studies implement the identification of spatiotemporal trajectories [43] and try to identify the depth maps of the captured movement, extraction of key poses, and positioning of body joints. It is worth noting that the activities with the highest number of publications in this review are mainly focused on health and rehabilitation topics. In one particular case study [18], the use of reflectors on specific body areas as reference points to identify the physical structure of one or more individuals for motion capture is used, providing a new capture methodology and tools for implementation and replication in future projects.

On the other hand, scholarly articles such as [23] and [42] explore the analysis of human activity using optical and microelectromechanical systems (MEMS) to compute the position and orientation of reference points within the body model. Similarly, works such as [29] and [41] refer to the aforementioned motion capture systems but focus on the study of the dynamic motion. Furthermore, studies such as [26] and [40] exclusively employ MEMS systems to evaluate the performance of physical activities in the realms of health, rehabilitation, or sports. Finally, articles such as [31]-[32], [43] investigate human activity through the application of Doppler detection and methods of classification of the obtained information. As such, Figure 10 provides a concise summary illustrating the distribution of technologies used for human activity analysis.

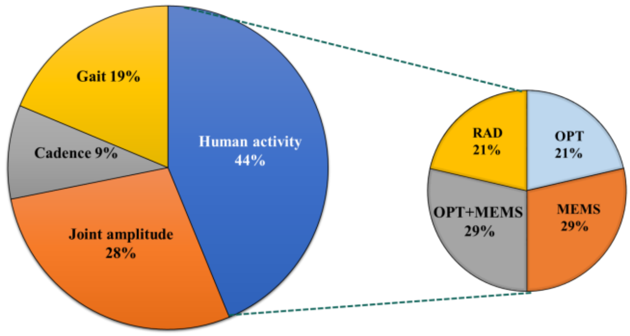

Fig. 10 Technologies implemented in human activity analysis (The authors)

3.4. Applications

The development of technologies capable of obtaining information through the mechanical movement of the physical structure of the human body has allowed the development of specific solutions to a problem affecting one or more fields. The most common applications include sports biomechanics, the study of professional training programs, rehabilitation environments, and entertainment industry [35], among others. In summary, Figure 11 shows that there is a trend in optical systems toward health and rehabilitation.

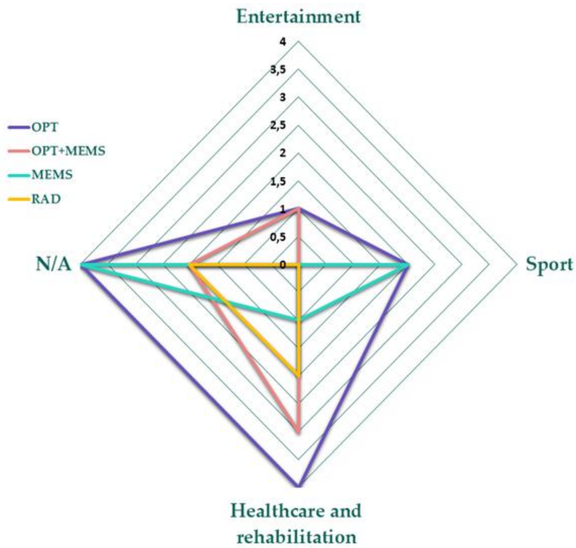

Fig. 11 A graphical representation of the most frequent applications found in the reviewed documents (The authors)

To better understand the importance of these technologies, specific applications of some items in this review are highlighted below.

3.4.1. Healthcare and Rehabilitation

The extension of human action recognition systems has been actively pursued in several applications. In this broad application segment, the monitoring of functional rehabilitation of patients with musculoskeletal disorders or physical disabilities that require comparative assessment of human movements stands out [34]. It is also known that the elderly population is beginning to have both physical and health problems. This is now a latent problem where motion tracking systems allow continuous monitoring [21], [33], enabling active and in some cases predictive identification of mobility limitations and timely intervention to restore impaired or lost activities of daily living (ADLs). Therefore, it is important to provide prompt and comprehensive medical care in the event of an emergency.

Other studies, such as [29], also offer fall detection systems that may temporarily reduce the need for medical care. There are now a variety of assistive devices that support rehabilitation from injury or disease, either in terms of data collection that a device provides through integrated wearable sensors or in the form of gait analysis-based systems [22], [24], [26], [36].

3.4.2. Sports

The technological development of noninvasive and low-cost systems has contributed to the collection of performance data in sports, whether during training or competition [38].

In equine training, for example, muscle use, posture, and tacit communication with the horse are all considered. In [19], the horse’s gait is analyzed and classified using machine learning and motion capture systems. Three methods (wavelet packet, statistical value, and an ensemble model) and mean square error cross entropy were used to improve and quantify the classification performance.

Digitization and motion analysis in martial arts also has a great opportunity with the use of these technologies to modernize the method of learning complex motor skills whose movements are predefined, constrained, and governed by physical laws. For example, a detailed analysis of psychomotor performance in karate fights can indicate whether the execution was good in practice, which can be supported by the use of optical recording systems [39]. However, they can be used by martial artists of different ages (children, adolescents, and adults) and performance levels to obtain a detailed performance assessment of the execution of different techniques as a function of the body movement used [37].

3.4.3. Entertainment

In the same way that dance is a form of artistic expression that uses the movement of the body to express an idea, an event, or a story, folkloric dance is considered cultural heritage because it contains living traditions or expressions that have been inherited from ancestors and can be passed on to future generations. For this reason, ways to immortalize such movements through digitization and visualization are currently being explored academically and scientifically [20], recognizing that body expression, expressed in terms of spatial positions and joint angles, is a relevant research area [17].

4. Discussion

Considering the current rise of numerous technologies that allow the acquisition of anthropometric variables of the human body for various applications, it should be noted that optical systems (OPT) based on markers are one of the most common methods for tracking body position [17]-[18], [22]-[24], [38], [45]. This type of motion capture is considered to be one of the most useful tools, allowing the study of motion to be focused on a specific area, segmenting and discarding unusable information. In some cases, it is obvious that the positioning of these markers can lead to inconveniences or discomfort that prevent the capture of the natural movement of the human body.

Regarding the techniques used to digitally process the collected information, the use of neural networks allows a novel technology to capture the body schema without optical markers [35], [43]-[45]. It is observed that deep learning provides an accurate and reliable estimation of body posture in the different models presented in the literature [5], [33], [36], [38], [46]. It is also possible to show the benefits of using intelligent algorithms, such as process automation, reduction of human error, faster motion analysis, and better information processing. In addition, the development and training of neural network-based algorithms can be costly, which prevents this technology from being widely available.

There is also a clear trend toward the use of generic intelligent algorithms (without the specific use of neural networks) since this technology offers a high degree of efficiency and improves several anthropometric measurement methods described in the literature [2], [20], [28], [31]-[32], [35], [37], [39], [43]-[44], [49]-[50]. Among these algorithms are those for filtering or noise reduction [8] or those for three-dimensional reconstruction of full body motion [23], [36]-[37].

Regardless of the processing techniques used to analyze the digital information, the collected data usually have weaknesses that affect the reliability in certain cases. However, optical systems have a latent error in capturing the motion in an image because some points are outside the two-dimensional boundary of the plane; therefore, it is impossible to obtain reliable data with a single camera. Several papers propose solutions based on the use of multiple cameras and sensors that can detect blind spots. A common solution is to use non-optical technologies with the implementation of other MEMS-based motion detection systems that compensate for the shortcomings of incomplete data obtained by optical systems [22], [47]. However, in recent years, Doppler detection systems have been implemented to complement missing information due to occlusion [43].

MEMS-based systems are also considered in the literature as a widely used and versatile technology. Although their emergence is not new, they are still used today due to their high sampling rates and accuracy of estimation on a short time scale [40]. However, these systems can still be subject to errors such as inaccurate data acquisition due to poor device placement, lack of module calibration, or strong magnetic interference [46], so the fusion of different motion sensing mechanisms is seen as a possible solution to some of the aforementioned errors [23], [29].

Most papers present various features of both optical and MEMS-based systems, considering aspects such as technology transferability, ease of use, and signal acquisition advantages. The need for practical and easily portable devices in fields such as medicine is emphasized. Several studies deal with health and rehabilitation [21]-[22], [26], [30], [34], where some of these features of motion capture devices are emphasized. Finally, it should be noted that some of the current features of motion capture systems are not unique to specific domains but can also be found in other industries, such as body motion analysis in entertainment, sports, or simply for research purposes with multiple applications [17, 19,20, 28, 39, 41].

From the review performed in this paper, it is considered advisable to continue exploring the fusion of different systems for motion capture of the human lower limbs, since although some works address the inclusion of more than one system [22-23, 28-29,32,43 51], few studies deal exclusively with the analysis of the lower limbs [29]. On the other hand, there is a latent need to deepen the portability of the devices, since the advances in this area are not so remarkable in the industry, although it is a highly desired feature.

5. Conclusions

In recent years, the evaluation of human motion has gained significant importance in various fields such as sports, health, industry, and entertainment. This article reviews the literature on technologies that facilitate the acquisition of information for the analysis of human motion, specifically in the lower body, through optical systems (OPT), radar systems (RAD), and inertial systems (MEMS).

The literature review revealed that optical motion capture systems constituted 41% of the technologies used in the reviewed studies. Notably, there has been a growing trend toward markerless systems since 2019. MEMS-based inertial magnetic sensor (IMU) systems accounted for 24% of the technologies employed, while radar sensors represented 14%. Additionally, 21% of the literature discussed the use of mixed systems that combine optical and MEMS detectors, offering potential solutions to individual system limitations.

This article provides a comprehensive and well-organized summary of the characteristics associated with each motion capture system. It explored aspects such as depth sensors, involved companies, device development, commercialization, specific features like marker implementation, and the type of analysis conducted in each study.

Despite variations in operational technologies and capture applications, human motion capture systems exhibit promising prospects. Continued efforts are required to enhance the reliability, versatility, cost-effectiveness and analysis techniques. These advancements aim to extract valuable information without imposing high computational costs.

This article stands out among other studies in the field by consolidating valuable information from existing literature, serving as a valuable resource for researchers and practitioners seeking to understand the capabilities and limitations of various motion capture systems, particularly in the analysis of the lower limbs.

The implications of this study extend to multiple fields, such as sports, health, industry, and entertainment, where the evaluation and analysis of human motion play a crucial role in driving improvements in performance, injury prevention, ergonomics, and entertainment experiences. By shedding light on the current state of motion capture technologies, the findings of this study contribute to the advancement of these areas.

However, the study’s reliance on existing literature could limit the scope of perspectives, and its specific focus on the lower body may not fully encompass the broader applications of motion capture technology. Furthermore, while the article provides a comprehensive overview, it does not extensively explore the technical intricacies or address the specific challenges associated with each system.

As a recommendation for future work, additional research should focus on further exploring the development of motion capture systems. Emphasis should be placed on enhancing reliability, versatility, and cost reduction while refining analysis techniques. Furthermore, research into overcoming the individual limitations of each system through hybrid approaches is warranted. These advancements will ultimately facilitate the extraction of valuable information from human motion analysis while minimizing computational burdens.

References

[1] CALLEJAS-CUERVO M, VÉLEZ-GUERRERO M A, and ALARCÓN-ALDANA A C. Proposal for Gait Analysis

Using Fusion of Inertial-Magnetic and Optical Sensors. *Revista EIA*, 2020, 17(34): 1-11, https://doi.org/10.24050/reia.v17i34.1472.
[2] AZHAND A, RABE S, MÜLLER S, SATTLER I, and HEIMANN-STEINERT A. Algorithm based on one monocular video delivers highly valid and reliable gait parameters. *Scientific Reports*, 2021, 11(1): 1-10, https://doi.org/10.1038/s41598-021-93530-z.
[3] FLERON M K, UBBESEN N C H, BATTISTELLA F, et al. Accuracy between optical and inertial motion capture systems for assessing trunk speed during preferred gait and transition periods. *Sports Biomechanics*, 2019, 18(4): 366-377, https://doi.org/10.1080/14763141.2017.1409259.
[4] GUTTA V, BADDOUR N, FALLAVOLLITA P, and LEMAIRE E. Multiple depth sensor setup and synchronization for marker-less 3D human foot tracking in a hallway. *Proceedings of the 2019 IEEE/ACM 1st International Workshop on Software Engineering for Healthcare*, SEH 2019). 2019, 77-80, https://doi.org/10.1109/SEH.2019.00021.
[5] ESTEVA A, et al. Deep learning-enabled medical computer vision. *NPJ Digital Medicine*, 2021, 4(1): 1-9, https://doi.org/ 10.1038/s41746-020-00376-2.
[6] Physiopedia. The emerging role of Microsoft Kinect in physiotherapy rehabilitation for stroke patients. https://www.physio-pedia.com/The_emerging_role_of_Microsoft_Kinect_in_physiotherapy_rehabilitation_for_stroke_patients (accessed Jun. 15, 2022).
[7] MIRON A, SADAWI N, ISMAIL W, et al. Intellirehabds (Irds)—a dataset of physical rehabilitation movements. *Data (Basel)*, 2021, 6(5): 1–13, https://doi.org/10.3390/DATA6050046.
[8] CHIANG A T, CHEN Q, WANG Y, and FU M R. Kinect-Based In-Home Exercise System for Lymphatic Health and Lymphedema Intervention. *IEEE Journal of Translational Engineering in Health and Medicine*, 2018, 6(October): 1-13, https://doi.org/10.1109/JTEHM.2018.2859992.
[9] ARMITANO-LAGO C, WILLOUGHBY D, and KIEFER A W. A SWOT Analysis of Portable and Low-Cost Markerless Motion Capture Systems to Assess Lower-Limb Musculoskeletal Kinematics in Sport. *Frontiers in Sports and Active Living*, 2022, 3(January): 1-14, https://doi.org/10.3389/fspor.2021.809898.
[10] YADAV S K, SINGH A, GUPTA A, and RAHEJA J L. Real-time Yoga recognition using deep learning. *Neural Computing and Applications*, 2019, 31(12): 9349-9361, https://doi.org/10.1007/s00521-019-04232-7.
[11] BLANCHARD N, SKINNER K, KEMP A, et al. Keep me in, Coach!': A computer vision perspective on assessing ACL injury risk in female athletes. *Proceedings of the 2019 IEEE Winter Conference on Applications of Computer Vision*, WACV 2019): 1366-1374, https://doi.org/10.1109/WACV.2019.00150.
[12] VALENCIA-MARIN C K, PULGARIN-GIRALDO J D, VELASQUEZ-MARTINEZ L F, et al. An enhanced joint Hilbert embedding-based metric to support mocap data classification with preserved interpretability. *Sensors*, 2021, 21(13): 1-17, https://doi.org/10.3390/s21134443.
[13] CLARK R A, MENTIPLAY B F, HOUGH E, and PUA Y H. Three-dimensional cameras and skeleton pose tracking for physical function assessment: A review of uses, validity, current developments and Kinect alternatives. *Gait Posture*, 2019, 68: 193-200, https://doi.org/10.1016/j.gaitpost.2018.11.029.
[14] JI X, ZHAO Q, CHENG J, and MA C. Exploiting spatio-temporal representation for 3D human action recognition from depth map sequences. Knowledge-Based Systems, 2021, 227: 107040, https://doi.org/10.1016/j.knosys.2021.107040.
[15] ZHANG L, XIA H, and QIAO Y. Texture Synthesis Repair of RealSense D435i Depth Images with Object-Oriented RGB Image Segmentation. *Sensors*, 2020, 20(23): 6725, https://doi.org/10.3390/s20236725.
[16] URRUTIA G, and BONFILL X. PRISMA declaration: A proposal to improve the publication of systematic reviews and meta-analyses. *Medicina Clínica*, 2010, 135(11): 507-511. https://doi.org/10.1016/j.medcli.2010.01.015
[17] KIM D, KIM D H, and KWAK K C. Classification of K-pop dance movements based on skeleton information obtained by a Kinect sensor. *Sensors* (Switzerland), 2017, 17(6): 1261, https://doi.org/10.3390/s17061261.
[18] CHATZITOFIS A, ZARPALAS D, KOLLIAS S, and DARAS P. Deepmocap: Deep optical motion capture using multiple depth sensors and retro-reflectors. *Sensors* (Switzerland), 2019, 19(2): 1-26, https://doi.org/10.3390/s19020282.
[19] LEE J N, BYEON Y H, and Kwak K C. Design of ensemble stacked auto-encoder for classification of horse gaits with MEMS inertial sensor technology. *Micromachines* (Basel), 2018, 9(8): 411, https://doi.org/10.3390/mi9080411.
[20] KICO I, GRAMMALIDIS N, CHRISTIDIS Y, and LIAROKAPIS F. Digitization and visualization of folk dances in cultural heritage: A review. *Inventions*, 2018, 3(4): 72, https://doi.org/10.3390/inventions3040072.
[21] FAISAL A I, MAJUMDER S, MONDAL T, COWAN D, and NASEH S. Monitoring Methods of Human Body Joints. *Sensors* (Switzerland), 2019, 19(11): 2629; https://doi.org/10.3390/s19112629.
[22] YANG C, et al. Physical extraction and feature fusion for multi-mode signals in a measurement system for patients in rehabilitation exoskeleton. *Sensors* (Switzerland), 2018, 18(8): 2588, https://doi.org/10.3390/s18082588.
[23] KAICHI T, MARUYAMA T, TADA M, and SAITO H. Resolving position ambiguity of imu-based human pose with a single RGB camera. *Sensors* (Switzerland), 2020, 20(19): 5453, https://doi.org/10.3390/s20195453.
[24] CIMOLIN V, et al. Computation of Gait Parameters in Post Stroke and Parkinson's Disease: A Comparative Study Using RGB-D Sensors and Optoelectronic Systems. *Sensors*, 2022, 22(3): 824, https://doi.org/10.3390/s22030824.
[25] PHAM T T, and SUH Y S. Spline function simulation data generation for walking motion using foot-mounted inertial sensors. *Electronics* (Switzerland), 2019, 8(1): 18, https://doi.org/10.3390/electronics8010018.
[26] ANCANS A, GREITANS M, CACURS R, et al. Wearable sensor clothing for body movement measurement during physical activities in healthcare. *Sensors*, 2021, 21(6): 2068, https://doi.org/10.3390/s21062068.
[27] SOLTANINEJAD S, CHENG I, and BASU A. Kin-FOG: Automatic simulated freezing of gait (FOG) assessment system for Parkinson's disease. *Sensors* (Switzerland), 2019, 19(10): 2416, https://doi.org/10.3390/s19102416.
[28] EHATISHAM-UL-HAQ M, et al. Robust Human Activity Recognition Using Multimodal Feature-Level Fusion. *IEEE Access*, 2019, 7: 60736-60751,

https://doi.org/10.1109/ACCESS.2019.2913393.
[29] PONCE H, MARTÍNEZ-VILLASEÑOR L, and NUÑEZ-MARTÍNEZ J. Sensor location analysis and minimal deployment for fall detection system. *IEEE Access*, 2020, 8: 166678-166691, https://doi.org/10.1109/ACCESS.2020.3022971.
[30] QIU S, WANG Z, ZHAO H, LIU L, and JIANG Y. Using Body-Worn Sensors for Preliminary Rehabilitation Assessment in Stroke Victims with Gait Impairment. *IEEE Access*, 2018, 6: 31249-31258, https://doi.org/10.1109/ACCESS.2018.2816816.
[31] LI W, TAN B, and PIECHOCKI R. Passive Radar for Opportunistic Monitoring in E-Health Applications. *IEEE Journal of Translational Engineering in Health and Medicine*, 2018, 6: 1-10, https://doi.org/10.1109/JTEHM.2018.2791609.
[32] LI H, SHRESTHA A, HEIDARI H, et al. Magnetic and Radar Sensing for Multimodal Remote Health Monitoring. *IEEE Sensors Journal*, 2019, 19(20): 8979-8989, https://doi.org/10.1109/JSEN.2018.2872894.
[33] CLIMENT-PÉREZ P, SPINSANTE S, MIHAILIDIS A, and FLOREZ-REVUELTA F. A review on video-based active and assisted living technologies for automated lifelogging. *Expert Systems with Applications*, 2020, 139: 112847, https://doi.org/10.1016/j.eswa.2019.112847.
[34] DEBNATH B, O'BRIEN M, YAMAGUCHI M, and BEHERA A. A review of computer vision-based approaches for physical rehabilitation and assessment. *Multimedia Systems*, 2022, 28: 209-239, https://doi.org/10.1007/s00530-021-00815-4.
[35] COLYER S L, EVANS M, COSKER D P, and SALO A I T. A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods towards Developing a Markerless System. *Sports Medicine – Open*, 2018, 4: 24, https://doi.org/10.1186/s40798-018-0139-y
[36] MORO M, MARCHESI G, HESSE F, et al. Markerless vs. Marker-Based Gait Analysis: A Proof of Concept Study. *Sensors*, 2022, 22(5): 2011, https://doi.org/10.3390/s22052011
[37] SZCZĘSNA A, BŁASZCZYSZYN M, and PAWLYTA M. Optical motion capture dataset of selected techniques in beginner and advanced Kyokushin karate athletes. *Scientific Data*, 2021, 8(1): 2-8, https://doi.org/10.1038/s41597-021-00801-5.
[38] GHADI Y, AKHTER I, ALARFAJ M, et al. Syntactic model-based human body 3D reconstruction and event classification via association based features mining and deep learning. *PeerJ Computer Science*, 2021, 7: 1-36, https://doi.org/10.7717/PEERJ-CS.764.
[39] ECHEVERRIA J, and SANTOS O C. Toward modeling psychomotor performance in karate combats using computer vision pose estimation. *Sensors*, 2021, 21(24): 1–27, https://doi.org/10.3390/s21248378.
[40] CAMOMILLA V, BERGAMINI E, FANTOZZI S, and VANNOZZI G. Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. *Sensors* (Switzerland), 2018, 18(3): 873 https://doi.org/10.3390/s18030873.
[41] YUAN Q, ASADI E, LU Q, et al. Uncertainty-Based IMU Orientation Tracking Algorithm for Dynamic Motions. *IEEE/ASME Transactions on Mechatronics*, 2019, 24(2): 872-882, https://doi.org/10.1109/TMECH.2019.2892069.
[42] KOK M, HOL J D, and SCHÖN T B. Using inertial sensors for position and orientation estimation. *Foundations and Trends in Signal Processing*, 2017, 11(1-2): 1-153, https://doi.org/10.1561/2000000094.
[43] AHUJA K, JIANG Y, GOEL M, and HARRISON C. Vid2doppler: Synthesizing doppler radar data from videos for training privacy-preserving activity recognition. *Proceedings of the Conference on Human Factors in Computing Systems* - 2021, https://doi.org/10.1145/3411764.3445138.
[44] SONG Y, JIN T, DAI Y, et al. Through-wall human pose reconstruction via UWB mimo radar and 3D CNN. *Remote Sensing* (Basel), 2021, 13(2): 1-22, https://doi.org/10.3390/rs13020241.
[45] ELAOUD A, BARHOUMI W, DRIRA H, and ZAGROUBA E. Weighted linear combination of distances within two manifolds for 3D human action recognition. VISIGRAPP 2019 - *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, 2019, 5: 693-703, https://doi.org/10.5220/0007369006930703.

参考文:

[1] CALLEJAS-CUERVO M、VÉLEZ-GUERRERO M A 和 ALARCÓN-ALDANA A C。使用惯性磁和光学传感器融合进行步态分析的提案。环评报告，2020，17(34)：1-11，https://doi.org/10.24050/reia.v17i34.1472。
[2] AZHAND A、RABE S、MÜLLER S、SATTLER I 和 HEIMANN-STEINERT A。基于单目视频的算法可提供高度有效且可靠的步态参数。科学报告，2021，11(1)：1-10，https://doi.org/10.1038/s41598-021-93530-z。
[3] FLERON M K、UBBESEN N CH、BATTISTELLA F 等。光学和惯性运动捕捉系统之间的准确性，用于评估首选步态和过渡期间的躯干速度。运动生物力学, 2019, 18(4): 366-377, https://doi.org/10.1080/14763141.2017.1409259。
[4] GUTTA V、BADDOUR N、FALLAVOLLITA P 和 LEMAIRE E。用于走廊中无标记3D人体足部跟踪的多个深度传感器设置和同步。2019 IEEE/ACM第一届医疗保健软件工程国际研讨会论文集，SEH 2019）。2019，77-80，https://doi.org/10.1109/SEH.2019.00021。
[5] ESTEVA A 等。支持深度学习的医学计算机视觉。NPJ数字医学，2021，4(1)：1-9，https://doi.org/10.1038/s41746-020-00376-2。
[6] 生理百科。微软体感在中风患者物理治疗康复中的新兴作用。https://www.psyo-

pedia.com/The_emerging_role_of_Microsoft_Kinect_in_physicaltherapy_rehabilitation_for_中风_患者（访问日期：2022年6月15日）。

[7] MIRON A、SADAWI N、ISMAIL W 等。智能康复(电流)—物理康复运动数据集。数据（巴塞尔），2021，6(5)：1–13，https://doi.org/10.3390/DATA6050046。

[8] CHIANG AT, CHEN Q, WANG Y, 和 FU M R. 基于体感的家庭运动系统用于淋巴健康和淋巴水肿干预。IEEE健康与医学转化工程杂志，2018，6（10月）：1-13，https://doi.org/10.1109/JTEHM.2018.2859992。

[9] ARMITANO-LAGO C、WILLOUGHBY D 和 KIEFER A W。用于评估运动中下肢肌肉骨骼运动学的便携式低成本无标记运动捕捉系统的SWOT分析。体育和积极生活前沿，2022，3（一月）：1-14，https://doi.org/10.3389/fspor.2021.809898。

[10] YADAV SK、SINGH A、GUPTA A 和 RAHEJA J L。使用深度学习的实时瑜伽识别。神经计算与应用，2019，31(12)：9349-9361，https://doi.org/10.1007/s00521-019-04232-7。

[11] BLANCHARD N、SKINNER K、KEMP A 等。让我进来，教练！”：评估女运动员前交叉韧带损伤风险的计算机视觉视角。2019 IEEE计算机视觉应用冬季会议论文集（WACV 2019）：1366-1374，https://doi.org/10.1109/WACV.2019.00150。

[12] VALENCIA-MARIN C K、PULGARIN-GIRALDO J D、VELASQUEZ-MARTINEZ LF 等。增强的基于联合希尔伯特嵌入的度量，支持动作捕捉数据分类并保留可解释性。传感器，2021, 21(13)： 1-17， https://doi.org/10.3390/s21134443。

[13] CLARK R A、MENTIPLAY B F、HOUGH E 和 PUA Y H。用于身体功能评估的三维相机和骨骼姿势跟踪：用途、有效性、当前发展和体感替代品的回顾。步态姿势，2019，68：193-200，https://doi.org/10.1016/j.gaitpost.2018.11.029。

[14] JI X, ZHAO Q, CHENG J, 和 MA C. 利用时空表示从深度图序列进行3D人体动作识别。基于知识的系统，2021，227：107040，https://doi.org/10.1016/j.knosys.2021.107040。

[15] ZHANG L, XIA H, 和 QIAO Y. 基于面向对象的RGB图像分割的实感D435i深度图像的纹理合成修复。传感器，2020，20(23)：6725，https://doi.org/10.3390/s20236725。

[16] URRUTIA G 和 BONFILL X. 棱镜宣言：改进系统评价和荟萃分析出版的提案。临床医学，，2010，135(11)： 507-511。

[17] KIM D、KIM D H 和 KWAK K C。根据体感传感器获得的骨骼信息对韩国流行音乐舞蹈动作进行分类。传感器（瑞士），2017，17(6)：1261，https://doi.org/10.3390/s17061261。

[18] CHATZITOFIS A、ZARPALAS D、KOLLIAS S 和 DARAS P. 深动捕捉： 使用多个深度传感器和后向反射器进行深度光学运动捕捉。传感器（瑞士），2019，19(2)： 1-26， https://doi.org/10.3390/s19020282。

[19] LEE J N、BYEON Y H 和 Kwak K C。利用微机电系统惯性传感器技术对马步态进行分类的集成堆叠自动编码器的设计。微型机械（巴塞尔），2018，9(8)： 411， https://doi.org/10.3390/mi9080411。

[20] KICO I、GRAMMALIDIS N、CHRISTIDIS Y 和 LIAROKAPIS F。文化遗产中民间舞蹈的数字化和可视化： 综述。发明，2018，3(4)：72，https://doi.org/10.3390/inventions3040072。

[21] FAISAL A I、MAJUMDER S、MONDAL T、COWAN D 和 NASEH S。人体关节监测方法。传感器（瑞士），2019，19（11）：2629； https://doi.org/10.3390/s19112629。

[22] YANG C, 等. 康复外骨骼患者测量系统中多模信号的物理提取和特征融合。传感器（瑞士），2018, 18(8): 2588, https://doi.org/10.3390/s18082588.

[23] KAICHI T、MARUYAMA T、TADA M 和 SAITO H。使用单个RGB相机解决基于惯性测量单元的人体姿势的位置模糊性。传感器（瑞士）， 2020， 20(19)：5453，https://doi.org/10.3390/s20195453。

[24] CIMOLIN V 等。中风后和帕金森病的步态参数计算：使用RGB-D传感器和光电系统的比较研究. 传感器，2022，22(3)：824，https://doi.org/10.3390/s22030824。

[25] PHAM T T 和 SUH Y S。使用脚上安装的惯性传感器生成步行运动的样条函数模拟数据. 电子学（瑞士），2019，8(1)：18，https://doi.org/10.3390/electronics8010018。

[26] ANCANS A、GREITANS M、CACURS R 等。可穿戴传感器服装，用于医疗保健中身体活动期间的身体运动测量. 传感器，2021，21(6)：2068，https://doi.org/10.3390/s21062068。

[27] SOLTANINEJAD S、CHENG I 和 BASU A. 光纤陀螺仪：帕金森病自动模拟冻结步态(多雾路段)评估系统。传感器（瑞士），2019，19(10)：2416，https://doi.org/10.3390/s19102416。

[28] EHATISHAM-UL-HAQ M 等。使用多模态特征级融合的鲁棒人类活动识别. IEEE访问，2019，7：60736-60751，https://doi.org/10.1109/ACCESS.2019.2913393。

[29] PONCE H、MARTÍNEZ-VILLASEÑOR L 和 NUÑEZ-MARTÍNEZ J. 跌倒检测系统的传感器位置分析和最小部署。IEEE接入，2020，8：166678-166691，https://doi.org/10.1109/ACCESS.2020.3022971。

[30] QIU S, WANG Z, ZHAO H, LIU L, 和 JIANG Y. 使用穿戴式传感器对步态障碍的中风患者进行初步康复评估。IEEE访问，2018，6：31249-31258，https://doi.org/10.1109/ACCESS.2018.2816816。

[31] LI W、TAN B 和 PIECHOCKI R. 用于电子医疗应用中机会监测的无源雷达. IEEE 健康与医学转化工程杂志，2018，6：1-10，https://doi.org/10.1109/JTEHM.2018.2791609。

[32] LI H，SHRESTHA A，HEIDARI H，等。用于多模式远程健康监测的磁和雷达传感。IEEE传感器杂志，2019，19(20)：8979-8989，https://doi.org/10.1109/JSEN.2018.2872894。

[33] CLIMENT-PÉREZ P、SPINSANTE S、MIHAILIDIS A 和 FLOREZ-REVUELTA F. 关于用于自动生活记录的基于视频的主动和辅助生活技术的综述。专家系统与应用，2020，139：112847，https://doi.org/10.1016/j.eswa.2019.112847。

[34] DEBNATH B、O'BRIEN M、YAMAGUCHI M 和 BEHERA A. 基于计算机视觉的身体康复和评估方法的综述. 多媒体系统，2022，28：209-239，https://doi.org/10.1007/s00530-021-00815-4。

[35] COLYER SL、EVANS M、COSKER DP 和 SALO A I T. 基于视觉的运动分析的演变和先进计算机视觉方法的集成对开发无标记系统的回顾。运动医学–公开，2018，4：24，https://doi.org/10.1186/s40798-018-0139-y

[36] MORO M、MARCHESI G、HESSE F 等。无标记与基于标记的步态分析：概念研究证明. 传感器，2022，22(5)：2011，https://doi.org/10.3390/s22052011

[37] SZCZĘSNA A、BŁASZCZYSZYN M 和 PAWLYTA M. 初级和高级极真空手道运动员所选技术的光学动作捕捉数据集。科学数据，2021，8(1)：2-8，https://doi.org/10.1038/s41597-021-00801-5。

[38] GHADI Y、AKHTER I、ALARFAJ M 等。通过基于关联的特征挖掘和深度学习进行基于句法模型的人体3D重建和事件分类。同行杂志计算机科学，2021，7：1-36，https://doi.org/10.7717/PEERJ-CS.764。

[39] ECHEVERRIA J 和 SANTOS O C。使用计算机视觉姿势估计对空手道战斗中的精神运动表现进行建模。传感器，2021，21(24)：1–27，https://doi.org/10.3390/s21248378。

[40] CAMOMILLA V、BERGAMINI E、FANTOZZI S 和 VANNOZZI G. 支持现场使用可穿戴惯性传感器进行运动表现评估的趋势：系统评价. 传感器（瑞士），2018，18(3)：873, https://doi.org/10.3390/s18030873。

[41] YUAN Q, ASADI E, LU Q, 等。基于不确定性的惯性测量单元动态运动方向跟踪算法. IEEE/美国机械工程师协会机电一体化学报，2019，24(2)：872-882，https://doi.org/10.1109/TMECH.2019.2892069。

[42] KOK M、HOL J D, 和 SCHÖN T B. 使用惯性传感器进行位置和方向估计. 信号处理基础与趋势，2017，11(1-2)：1-153，https://doi.org/10.1561/2000000094。

[43] AHUJA K、JIANG Y、GOEL M 和 HARRISON C. 视频多普勒：从视频中合成多普勒雷达数据，用于训练隐私保护活动识别。计算系统中的人为因素会议论文集-2021，https://doi.org/10.1145/3411764.3445138。

[44] SONG Y, JIN T, DAI Y, 等。通过超宽带多输入多输出雷达和3D美国有线电视新闻网进行穿墙人体姿势重建。遥感（巴塞尔），2021，13(2)：1-22，https://doi.org/10.3390/rs13020241。

[45] ELAOUD A、BARHOUMI W、DRIRA H 和 ZAGROUBA E. 用于3D人类动作识别的两个流形内距离的加权线性组合。视觉格拉普2019-第十四届计算机视觉、成像与计算机图形理论与应用国际联合会议论文集，2019，5：693-703，

https://doi.org/10.5220/0007369006930703。