

Review

The Role of Emergent Technologies in the Dynamic and Kinematic Assessment of Human Movement in Sport and Clinical Applications

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Abstract: Physical activity analysis assessment has been a concern throughout human history. The intersection of technological growth with sports has given rise to a burgeoning field known as sports engineering. In the 19th century, the advent of chrono-photography and pioneering marked the inception of sports performance analysis. In recent years, the noticeable developments achieved in wearable low-power electronics with wireless high interconnection capability, as a part of modern technologies, have aided us in studying sports parameters such as motor behavior, biomechanics, equipment design, and materials science, playing an essential role in the understanding of sports dynamics. This study aims to review over 250 published articles since 2018, focusing on utilizing and validating these emergent technologies in sports and clinical aspects. It is predicted that one of the next steps in sports technology and engineering development will be using algorithms based on artificial intelligence to analyze the measurements obtained by multi-sensor systems (sensor fusion) to monitor biometric and physiological parameters in performance analysis and health assessments.

Keywords: sports engineering; wearable technology; internet of things; strain gauge; inertial measurement unit; localization systems; motion capture systems; sensor fusion; artificial intelligence



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1. Introduction

The exploration of human movement has a rich historical lineage [1]. From Aristotle, there are existing studies about anatomical, mechanical, and motion analysis and their function to find the possible link between anatomy and human movement, focusing on the problems related to the balance of human posture and daily actions. Successively, Giovanni Alfonso Borrelli presumed the importance of the lever arms of the musculoskeletal system in the production of movement [2].

Moving forward from human movement studies based on simple observation to initial kinetic and physiological measurements regulating human movement in the space-time domain, only in the 19th century did technologies and developed methods and proper devices appear. Eadweard Muybridge, the pioneer in motion capture in his famous experiments in 1878, set up a series of twelve cameras to record the gallop of a horse, showing the phase where all four hooves were off the ground [2,3]. In the same period, the French scientist Etienne-Jules Marey studied the locomotion of animals and humans. Based on the studies of Muybridge and Pierre Janssen, he developed chrono-photography, a technique to create scientific recordings, and a chronophotographic gun to take twelve photographs per second [4].

Despite the first dynamometer being invented by Regnier (1798) [5], the measurement of the muscular force developed during human locomotion was not investigated until Carlet of France (1872) used pneumatic bulbs attached to the foot to measure pressure under the heel and metatarsal regions [6]. Moreover, Jules Amar developed a device, the arthro-dynamometer, able to measure joint amplitudes and force variations based on their angle and, successively, he developed a three-component force plate using a mechanical–pneumatic system to measure the ground reaction force [7,8]. Since then, several similar force platforms have been described in the literature based on the function of extensometer load cells, allowing the assessment of different quantitative movements such as walking, sprinting, and jumping [9–12] until the introduction of piezoelectric force platforms by Kistler in 1969 [13]. Fatefully, the logistic conditions to measure jump or run performance on these expensive force platforms compelled the coaches and trainers to measure in controlled environments like sports institutes or university laboratories with limited access to all sports practitioners. To overcome this problem, in 1980, cheaper and easily accessible portable devices such as the conductance mat and, soon after, the optoelectronic bars were introduced to measure the kinematic parameters of jump and run performance directly in the competitions or training fields [14].

The electronic monitoring of dynamic muscular strength in flexo-extension limb movement was introduced with isokinetic apparatus [15] with the limit to assess muscular performance in an unnatural contraction regimen (constant velocity). Only in 1995 did Carmelo Bosco introduce a system based on the linear encoder that could determine the dynamic muscular performance in the natural isotonic contraction regimen [16]. Such a device is able, through an infrared photo interrupter, to measure the covered distance by a load in the function of the time and calculate velocity, force, and power during the concentric, eccentric, and stretch-shortening cycle contraction types to determine, with an increase loads test, the neuromuscular profile through the force–velocity, and power–velocity relationships introducing the power-based training method.

The birth of the internet characterizes the 20th century, and the resulting evolution will influence new devices of motor behavior and sports performance. Wearable devices, Internet of Things sensors (IoT—further explored in Section 3), and wireless technologies evolved to monitor the external and internal load, giving specificity to training load relative to the matches or race demands (Figure 1).

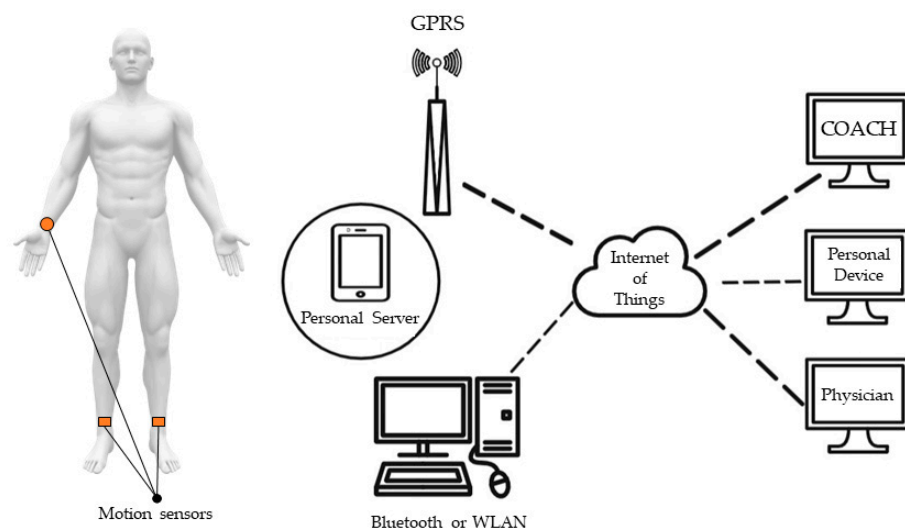


Figure 1. Outline of IoT system.

This new impulse has paved the way for new opportunities and challenges for the research and development of wearable devices into four major clusters: health, sports, daily physical activity, tracking and localization, and safety.

IoT technology, low-power wearable device development, and Data Acquisition (DAQ) are becoming increasingly commonplace in many sports [17–20]. One widely used device in these systems is the Inertial Measurement Unit (IMU—further explored in Section 5.1). Additionally, IMUs can be integrated with heart rate monitor systems, Global Navigation Satellite Systems (GNSS—further explored in Section 6.2) terminals, and sometimes frequency and force sensors. For example, kinematic DAQs, relying on GNSS and IMU or Ultra-wideband-based location systems (UWB—further explored in Section 6.1.3), are widely used in team sports such as rugby or football [21,22] to measure the position and displacement of the athletes on the pitch. Dynamic parameters can also be measured (e.g., the forces exerted on the oars in rowing [23] or on the paddle in flatwater kayaking [18,24]) employing strain gauge bridges, together with kinematic ones.

Considering that the latest versions of these applications are becoming more performant from this point of view, the accuracy and reliability of collected data have always been even more crucial [25]. In this context, the essential point by the coaches is to pay attention to discriminating relevant data from countless pieces of information [25]. This technology, widely employed in sports activities monitoring, has found applications in home-based telemedicine, especially suited for the population affected by chronic diseases, mainly if used together with cloud systems [25].

In the clinical area, wearable sensors and technologies are becoming valuable for physicians and physiotherapists to learn the patients' movements and design their rehabilitation methods [26].

Changes in daily physical activities, such as time spent walking, distance, pace, speed, elevation, calories burned, and heart rate, are easily accessible even by smartphone apps or worn waistbands and skin patches connected to it via radio links. They can measure different aspects of performance during all kinds of physical activities [27]. Furthermore, IoT has played a significant role in developing the Internet of Medical Things, facilitating remote healthcare, edible sensor tracking, and mobile health applications. This integrated system enables the measurement of vital signs, which is crucial for physicians to monitor and assess patients' well-being remotely.

In this study, over 250 papers were selected through a search strategy considering the keywords related to the field of human performance assessment, modern technologies, and devices to underline the actual state of human movements monitoring in different conditions, looking to identify the actual advances in sports technology applicable in sport, wellbeing, and clinical field published in the last five years. Differently from the current literature, in which the authors focused on specific devices such as wearable sensors to mainly monitor sport and fitness performance [28–30], this review aims to provide a wide global vision of the recently available technologies that are applied in sport, fitness, and clinical fields to monitoring human motion performance.

2. Materials and Methods

2.1. Inclusion and Exclusion Criteria

The article's selection process framework focused on study design, comparison, outcomes, and interventions. All the papers were published in English with content on technologies for elite and recreational players and patients with physical disorders. These studies are focused on analyzing players' performance enhancement using tools and individual or sports teams' technical and tactical performance through match, training, or lab environment analysis.

2.2. Search Strategy and Review Process

The paper selection process has been performed by several databases such as PubMed, World of Science, Science Direct, and IEEE Xplore since 2018. The keywords related to wearable technologies in sports and physical activities included an accelerometer, gyroscope, IMUs, wearable sensors, wearable systems, and sports technology (Table 1). This article reviewed the papers by matching the keywords to the title, abstract, and keyword fields.

Table 1. Boolean search strategy.

Databases	Keywords ¹
Pub Med	("accelerometry" OR "accelerometer" OR "gyroscope" OR "inertial sensor" OR "inertial measurement unit" OR "wearable sensor" OR "wearable system" OR "sports technology" OR "wearable device" OR "IMU" OR "MEMS" OR "GPS" OR "GNSS" AND "Sports" OR "UWB" AND "Sports OR "smart device" AND "workout" OR "smart insole" AND "pressure detection" AND "Parkinson" AND "Diabetic Feet" AND "posture" OR "Football" AND "TRACAB" OR "video tracking systems" OR "GPS device" OR "video technology" AND "soccer")
World of Science	("accelerometry" OR "accelerometer" OR "gyroscope" OR "inertial sensor" OR "inertial measurement unit" OR "wearable sensor" OR "wearable system" OR "wearable device" OR "IMU" OR "MEMS" OR "GPS" OR "GNSS" AND "Sports" OR "UWB" AND "Sports OR "sports technology")
Science Direct	("wearable sports technology" OR "Sports measurement units" OR "sports technology" OR "accelerometry" OR "inertial measurement unit" OR "GPS" OR "GNSS" AND "Sports" OR "UWB" AND "Sports OR "smart insole" AND "pressure detection" AND "Diabetic Feet" AND "posture" OR "Biomechanics" OR "Sprint kayaking" OR "Instrumentation" OR "Measurement" OR "markerless" OR "Inertial sensor" OR "Basketball sensing")
IEEE Xplore	("wearable sports technology" OR "Sports measurement units" OR "sports technology" OR "accelerometry" OR "GPS" OR "GNSS" AND "Sports" OR "UWB" AND "Sports OR "inertial measurement unit" OR "deep learning" OR "Kinematics" AND "Software" OR "Sensor systems" OR "Sensors" OR "Performance Assessment" OR "Flatwater Sprint Kayak" AND "Data Acquisition System" OR "ultra-wideband" OR "wireless positioning" OR "wireless sensor networks" OR "Internet of Things" OR "Wireless communication" OR "Bluetooth")
MDPI Open Access Journal	("Ultra-Wideband" OR "localization" OR "positioning" OR "indoor positioning" OR "wireless sensor networks" OR "wearable computing" OR "performance analysis" OR "flatwater kayaking" OR "motion capture" OR "deep learning" OR "retro-reflective markers" OR "multiple depth sensors" OR "deep mocap" OR "sensor fusion" OR "bending strain" OR "dielectric elastomer sensors" OR "wearable sensors" OR "foot pressure distribution" OR "gait analysis" OR "pressure sensor" AND "bio-medical applications" OR "baseball pitching" OR "ball speed generation" OR "ice hockey" OR "IMU")
Hindawi	("Wearable Inertial Sensors" OR "IMU" AND "Sport" OR "Microsoft Kinect" AND "Postural Disorder Assessment" OR "Gait Abnormality")
Taylor & Francis	("Assessment" OR "game analysis" OR "technology" OR "team sport" OR "Motion analysis" OR "kinematics" OR "movement" AND "tennis" OR "sports" OR "Canoe sprint" OR "kinematic analysis")
ResearchGate	("Beacon" OR "positioning" AND "Basketball" OR "GPS" OR "Soccer" AND "Performance analysis")

¹ Limit to English.

The experimental studies selected for this review primarily followed two characteristics of experiments. The first was applying wearable sensors to measure and analyze the player's performance. Second, the investigations compared wearable sensors with other gold-standard devices to ensure their validity and reliability.

2.3. Technique Analysis

This review's selected sports categories include water or snow, ball, racket or stick, combat, running and track and field, and weight exercises.

The study of sensors mainly focused on the team technical analysis, individual techniques of players' motion, the sports equipment efficiency, accuracy of the inertial sensors

by comparison via a gold standard, and health monitoring during physical activities. The aims of the related articles in each section are separately reported.

3. Wireless Sensor Networks (Internet of Things—IoT)

The IoT paradigm exploits multiple, often small, interconnected devices that work together with a shared job to enable seamless communication and cooperation. Rapid technological development in the wearable IoT industry has occurred in recent years. Some forecasts show a speedy increase in the budget and number of connected wearable devices worldwide in the following years (e.g., according to some market research, the market for wearable technology sensors will reach USD 6.1 billion in 2026 in the United States only) [31,32]. At the same time, because of this wide availability of low-cost, low-power, and lightweight devices, it has experienced an acceleration in the growth of an even more increasing number of IoT-based applications implementing not obstructive wearable sensors for both professional and recreational athletes [33,34]. As a result, many wirelessly connected sensors integrated into apparel and sports equipment have emerged. In this framework, two technologies are mainly used: Radio Frequency Identification (RFID) and wireless sensor networks (WSNs) [35]. For this purpose, specific studies on the features of the antennas (e.g., among the flexible, patch, monopole textile, or fully textile loop antennas) that can be safely used for body-worn wireless devices (e.g., they must present a value of specific absorption rate below the maximum limit allowed by the standards) have been carried out for applications in free space as well as on wireless body area network (WBAN) [35–43]. Furthermore, especially during the last COVID-19 pandemic, their employment in remote patient monitoring also significantly increased.

High sports performance requires advanced technologies, as each athlete tries to gain a competitive edge through incremental improvement. DAQ plays a fundamental role in this competitive environment, supplying athletes and coaches with quantitative insights into every performance aspect [36–38]. Nevertheless, collecting kinematic, dynamic, or physiological data during athletes' physical activities represents a critical issue when you need to avoid any alteration in the measure due to physical or psychological obstruction from applying any measurement system. Thus, IoT technology has brought the birth of several new unobtrusive DAQ systems, overcoming most of the drawbacks mentioned above. Consequently, in the sports community, the interest in this area and the requests to carry out reliable and trustworthy measures are now increasing among the coaches and the athletes themselves [39,40].

IoT devices in the sports industry aim to conduct performant devices wearable by the athletes or installed on equipment, such as smart bicycles, medical sensors, and fitness trackers that can acquire biological and biomechanical parameters and wirelessly send them to proper user terminals such as tablets, smartphones, and smartwatches. Variables such as heart rate, blood lactate, or training impulse to prevent injuries or position and trajectory tracking information of a ball, athlete movement pathway in individual games such as ski or team technical footpath such as football defenders are nowadays accessible via IoT technology [25,26].

Sensor Networks: Wireless Transmission Systems

The technological advances in miniaturized low-power sensors described in the previous section allowed the implementation of WBAN, or a simple body area network, suitable for applications in both medical and non-medical fields. These networks consist of sensors (whose number and nature continuously increase), embedded processors, and transceivers. In addition, they are featured to operate at low power consumption, allowing these devices to be supplied with small and light batteries that make possible an easy and unobtrusively wearing, enabling, at the same time, the simultaneous acquisition of biomechanical and health parameters and their routing to external (remote if it is required) systems for deeper analyses (e.g., the nearby hospital for electrocardiogram in heart disease patients) [43].

These sensitized systems developed for sports and medical applications usually feature a central unit (Master node) and a group of other nodes (the Slave nodes). The former oversees scheduling the DAQ for the whole WBAN and communicating with the user terminal, eventually hosting other sensors. The latter consists of a microcontroller unit that can handle one or more sensors in the node and the data transmission to the primary node [44]. These networks can be wired or radio-connected with the primary node for the data exchange (WSNs). These are particularly suitable in sports applications, as cables can hinder athletes' movements during training and competitions [45]. A WSN mounted on the same athlete where, by using more sensors (of the same or different type), several dynamic, kinematic, or physiological parameters are monitored is known as a Personal Area Network [46] or body sensor network [47]. The communication range represents, in this case, a particularly severe constraint where the body sensor network can cover a very short distance (Figure 2).

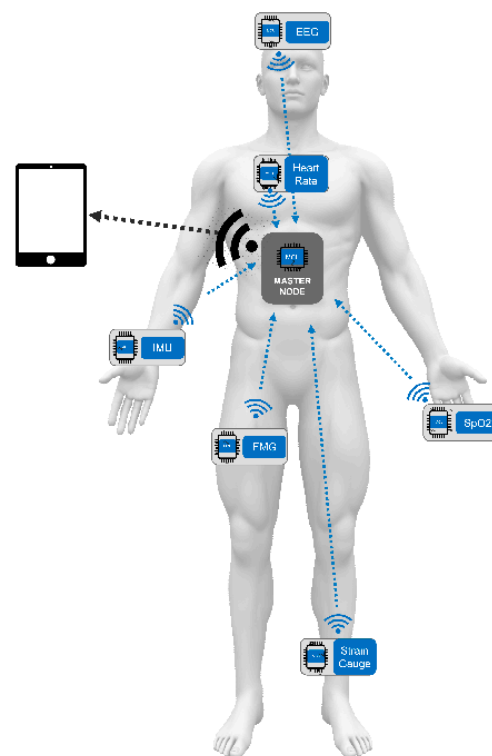


Figure 2. Example of a body sensor network.

Several wireless standardized sports protocols with different bands, data rates, transmission ranges, and network topologies are available [44]. Bluetooth, Wi-Fi, and ZigBee are wireless communication systems utilizing the Industrial, Scientific, and Medical (ISM) band [48]. However, until the early 2000s, no universal communication standard was suitable for sports and health applications developed among the leading vendors (Advanced and Adaptive Network Technology—ANT+) [49]. More recently, other systems based on common telecommunication standard protocols, such as ZigBee and Bluetooth, have been developed and put on the market. They can be effectively employed in low-power, low-bandwidth wireless mesh networking. Zigbee exploits the mesh network for data transmission over long distances by performing “hops” of the messages on intermediary radio nodes on the way to their destination [50].

Several systems on the market nowadays employ sensor networks based on these transmission protocols. Among the others is the Captiks system (further explored in Section 7.2), while, in [50], it is described as a sensor network based on ZigBee and designed for remote sports injury monitoring. In particular, the wireless nodes have a three-axial acceleration sensor to construct the human motion model exploiting a fifteen rigid bodies

model. Because of the limited number of nodes placed relatively close to one other, it does not require using typical routing characteristics of such a standard to improve transmission efficiency. Ref. [51] presents a wearable wireless system designed to implement a medical IoT for patient health parameters such as the electrocardiogram (ECG), temperature, blood pressure, and blood glucose monitoring.

Nowadays, there is fast growth in consumer portable devices in most daily activities, and remarkably, they have overcome the diffusion of these standards, such as ANT+ and ZigBee, since their communication protocols consist of Bluetooth and Wi-Fi only. As a result, the number of smartphone apps suited for connection with sports instrument equipment continues to grow. For example, after Apple Inc. began to sell its smartphone devices equipped with the Bluetooth Low Energy (BLE) protocol, several fitness products were developed with the same communication protocol to be compatible with these devices. In contrast, using ANT+ or ZigBee transmission protocols with a smartphone would require additional hardware [52].

Today, the design of a sensor network suited for sports applications must guarantee low power consumption of the wireless sensor nodes, wide transmission range between them, reconfigurability of the network allowing the easy addition of extra nodes, and, finally, the possibility of using personal portable terminals. Moreover, and primarily when the sensors must be placed at a great distance from each other, the design must care about the attenuation of the transmitted signal due to the obstacles between them as sports equipment, often manufactured with radio-shielding materials (e.g., among the others the carbon fiber), and the body of the athletes themselves. In addition, the design must consider the disturbance due to other radio transmissions in the nearby area and the similar frequency band as Wi-Fi or Bluetooth networks. In this case, the problem could be overcome by using more transmission nodes nearer distances and working as signal repeaters [44].

4. Dynamic Assessment of Movement Performance

In the history of the application and the development of new devices devoted to functional assessment, a relevant point was represented by introducing a force platform based on strain gauges [53] or piezoelectric crystals [54]. In the sport and rehabilitation field, the most used force platforms in the laboratory exploit strain gauges or load cells. They can measure the value sampled in time of the force components applied to them according to the three axes. By processing these values, proper software can compute several parameters useful for functional assessment [55]. In particular, the main parameters investigated were the vertical force, the impulse force, the peak of force, the rate of force development, the acceleration, the velocity, the power, and the displacement position change [56]. The sampling frequency range ranges between 50 and 1000 Hz and depends on how fast the movement is [57,58]. Sensor manufacturing has been sharply improved regarding developing low-cost and readily available materials, reducing the costs of purchasing resources and the time it takes to obtain them.

Furthermore, the study of joint movement structure via this type of sensor leads to understanding the case's deep posture patterns and position. For example, rehabilitation or utilizing the specific data of the several poses that can be obtained via bright gloves and smart insoles, electromyography (EMG) signals, heart rate, and muscle motion monitoring in the design for robotic control or design prosthesis devices for amputees [59–61].

4.1. Wearable Strain Gauges

A common concern of most athletes is that external sensors could affect their freedom of movement reduction [62]. For this purpose, strain gauges that can be applied directly on the skin of the human body or, thanks to knitted technology, inside the sports apparel, with high elasticity and without any sewing, resulting in noninvasive and comfortable wearable devices that can be effectively employed for the real-time assessment of a sports performance or the evaluation of a patient's physiological conditions [63]. The integration of smart sensors into sports garments occurs non-intrusively through the development

of textile sensors. These sensors are seamlessly incorporated into the fabric, allowing for discreet and unobtrusive monitoring of various parameters [60]. Gait analysis and standing posture detection are the most common pressure and force sensor applications in wearable DAQ systems. A further typical application of such types of sensors is related to the study of joint movements, attaching them directly to the skin surface of fingers, wrists, knees, or elbows or placed on gloves, knee sleeves, or elbow pads. They can be applied to monitor stress and strain on the body organs effectively during several sports activities like walking, running, squatting, jumping, and performing human–computer interactions [59].

4.1.1. Sensing Gloves

In the measurements of hands or finger motion, sensors with remarkably high sensitivity and fast response are required. One of these sensor systems has been manufactured by directly applying a thin film of conductive materials on a polymeric substrate. In [64], the role of wearable sensory gloves and sensory feedback devices is illustrated to understand the aids to process the prostheses production or impaired sensory limbs for the individual athlete and to characterize the instruments. The sensory gloves were designed by the strain gauge, pressure, and temperature to accomplish the movement analysis variables by receiving the vibrotactile and mechano-tactile feedback. In this example, the quality and structure of the sensory gloves were stretchable, flexible to fold and bend, gauge factors, power consumption, absorbent, and comfort (Figure 3).

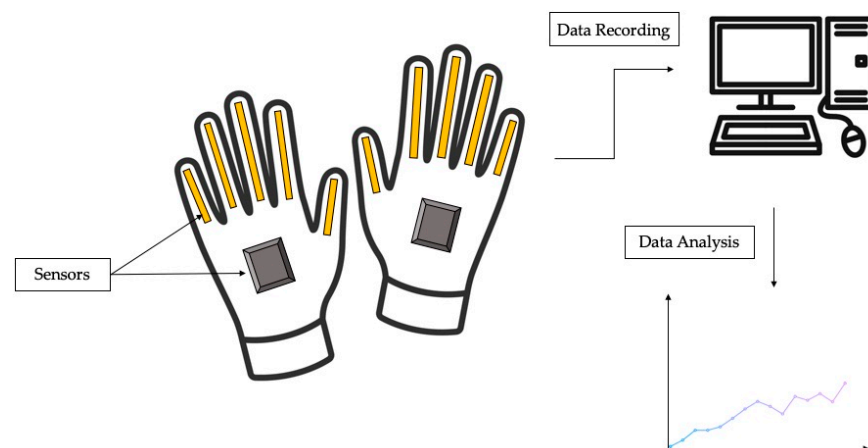


Figure 3. Sensing gloves are devices with more sensors attached to fingers and/or palms to track motions and obtain information about hands' behaviors.

In particular, in [61], the authors used a commercial glove made of Nitrile Butadiene Rubber, which has been spray coated with a patterned layer of conductive material through a stencil mask (i.e., Electroless Nickel Immersion Gold). In this way, the sensor shows a strain resistance response featured by two linear regions with an extremely high sensitivity value. Other authors present [60] prototype instrumented gloves that have been manufactured by a knitted process combining non-conductive yarn (i.e., polyester) and conductive yarn (i.e., 99% silver-coated nylon) with a 30 Ohm/cm linear resistance. Moreover, the resulting knitted structure is more elastic than other fabrics. Five sensors implemented with this technique were placed on the wrist and over the proximal interphalangeal and metacarpophalangeal joints of the four fingers and thumb. Although the conductive yarn presents a constant value for electrical resistivity and strength, it is possible to vary with the design of the sensor's shape, the number of contact points, and the contact pressure. Consequently, the electrical resistance of the contact can decrease with the increase in contact pressure and contact points inside the conductive knit.

Capturing hand kinematics is necessary for medical applications, such as rehabilitation and hand function evaluation [57], and determining the recovery progress of stroke patients' hands. Studies on hand kinematics capturing have used noncontact-based or wearable

technology [65–67]. Wearable systems offer a practical solution for capturing precise hand kinematics without being limited by environmental constraints. Physicians can effectively observe finger motions by utilizing sensors attached to the fingers of a data glove. This feature allows for accurate monitoring and analysis of hand movements without being hindered by external factors.

Sensor-based garments are ubiquitous due to the interest in wearable devices, which can be used to monitor human posture and gestures. The systems have evolved dramatically, and the recent advances in this area can be worn for a long time with non-discomfort [68]. Bioengineering places significant emphasis on monitoring human body kinematics, posture, and gestures. This focus area aims to develop techniques and technologies that precisely measure and analyze these aspects. By understanding and monitoring human movement, bioengineering contributes to various fields such as healthcare, rehabilitation, sports science, and ergonomics.

In [69], the wearable sensing glove for monitoring hand gestures and posture has been developed. The glove sensing capability is based on optical fiber Bragg gratings sensors. As the base structure is a standard glove, there are no significant issues concerning wearability. Plus, based on the strategy to apply the sensing structure, different gloves can be easily manufactured with varied sizes, materials, and styles. A glove incorporating a single optical fiber with Bragg structures positioned at specific spots, such as finger joints, was evaluated for its functionality and performance. The sensor response exhibited linearity with hand movements for opening and closing. This sensor response allowed for the extraction of joint angle information, enabling the estimation of parameters like finger force. The developed glove provided real-time numerical data on hand posture angles. Its simplicity and performance make it suitable for various applications, including physical therapy, studying human kinematics in sports, virtual reality, and remote-control applications. Additionally, as the fiber Bragg gratings only require a single optical fiber end to access the sensor response, the overall system becomes straightforward concerning construction and maneuverability, which are crucial requirements for possible applications.

Refs. [65,70] independently proposed data gloves with IMUs containing an accelerometer, gyroscope, and magnetometer. Two existing data gloves could accurately measure finger motion but had limitations such as wired transmission and restrictions during hand function evaluation tasks. Other authors proposed in [71] a low-cost data glove with nine-axis sensors, but dynamic validation was lacking, limiting its applicability in the medical field. Ref. [67] developed a pair of data gloves with an attitude measurement algorithm, conducting static and dynamic validation. However, the non-modular hardware design rendered the glove unusable if a sensor was damaged.

Considering the need for improvement in transmission methods and modular design, a hand-function assessment system was proposed [72]. This system utilized a data glove with six-axis IMUs, but it only had an accelerometer and gyroscope and could measure the Range of Motion (ROM) in specific settings. Furthermore, with only one IMU on the back of the hand, accurately capturing the ROM for the thumb and little finger's metacarpophalangeal joints was impossible.

4.1.2. Sensing Knee Bondages

Ref. [73] emphasizes the practicality of using a knee bandage as a wearable solution for capturing bio-signals and monitoring human activities and introduces the use of a knee bandage in the context of Human Activity Recognition (HAR) research. The introduced knee bandage (GenuTrain knee bandage provided by Bauerfeind AG), is utilized as a wearable carrier of sensors for the development of an end-to-end HAR system. The study goal is to assist in the early treatment of Gonarthrosis (known as knee osteoarthritis, which is a degenerative joint disease that affects the knee). The knee bandage incorporates sensors and bio-signal acquisition devices, such as electromyography electrodes, to capture data related to the user's movements such as walking, sitting to stand, or standing to sit. Throughout the research, the knee bandage serves as a platform for the implementation of

the HAR-based mobile technology system. The integration of bio-signal acquisition devices and sensors into the knee bandage and the placement of electromyography electrodes on the right leg are specifically explained in the article.

Additionally, in [74], the placement of body-worn sensors, including on the knees, is emphasized for sensor-based HAR, particularly in the context of gait analysis. Recognizing the pivotal role of the lower body, the article introduces a modeling scheme for gait-based activities, breaking down gait into two phases and five states. The chosen sensor positions below the waist are informed by the importance of understanding movements related to walking and other activities involving leg motion. This approach enables a detailed analysis of phases and states during activities like walking, emphasizing the significance of lower body sensor data for accurate and comprehensive HAR.

4.2. Strain Gauges in Instrumented Sports Equipment

The pressure sensors are operated through strain gauge sensors embedded inside the external sports tools such as paddles. These sensors measure the device's applied or received external pressures, enabling the detection of resistance changes in static, kinetic, or dynamic modes [24,75]. In the sports research of the strain gauges, ref. [24] operated this modern device for Kayak water sport. They mounted a strain gauge inside both the paddle and footrest to measure the forces acting on them. So, they can evaluate the crew's performances by computing other parameters (e.g., stroke frequency) or consider these measurement results with acceleration and roll, yaw, and boat pitch obtained by GNSS and IMU, respectively. The advantage of this experimentation in the pilot study is to analyze the boat motion in both dynamic and kinematic pathways, the kayak propulsion study, and the paddling technique of the athletes. In the same area of performance analysis in skiing, it is valuable to understand the snow and skier interactions. The attached strain gauge under the ski surface was allowed to measure the load evolution during turns, torque, and force distribution between the left and the right leg during the alpine skier's progress.

Additionally, this research area is beneficial to designing ski boots and bindings to enhance the athletes' approach [76]. The embedded strain gauge between the top of the tennis racket handle and the shaft bottom measured the estimated impact force in tennis forehand stroke. In the same area of research, the benefit can be understanding the technique to execute the tennis ball to reach the optimal speeds and modify a player's stroke technique [77]. In golf, more flexible shaft bending during the golf swing has a direct effect on making a more significant contribution to clubhead speed due to increasing the angular velocity at the grip. Via embedding the strain gauge inside the shaft of the golf stick, the data of the magnitude of shaft strain during the swing, rotation, and change in the shaft strain profile are accessible to aid in providing custom-fit clubs to golfers [78].

Performance awareness, sports posture, and medical injury analysis via applied pressure and force on the pedal-based strain gauge are advantageous to understanding the cyclist sport discipline and bike design to enhance performance and reduce injury risks. Configuration of the strain gauge on the pedal and correct set-up to discover the linear relationship between strain and force on the pedal shaft led the designers to produce the equipment and guide the coaches and athletes in their analysis sessions by measuring 3D applied forces on the pedal in the outdoor and laboratory conditions to allow to record pedal force patterns in actual conditions [79,80]. In [81], the deformation and elasticity of the pedal were measured via embedded strain gauges to determine 3D pedal loads for cyclists. The strain gauges were attached in the sagittal, frontal, and transversal planes to collect data on the medial-lateral, proximal-distal, and vertical forces. The injury risk is dependent on cycle design, cyclist posture, and seat type that occurs in the bottom area, knee and low-back pain, and, via strain gauge device, it is possible to measure the crank arm forces to explore standard pedal cycles related to the overuse injuries and muscle fatigue.

4.3. Wearable Pressure Sensors

Pressure sensors are measuring devices for the contact area and force test. The principle of pressure sensors, piezoresistive, capacitive, and piezoelectric, is like that of strain sensors. Usually, a pressure sensor consists of an electrode layer exploited to transmit signals and an active one that deforms under the action of the pressure and causes voltage changes in the output signal [82].

The most widespread application of pressure sensors is the monitoring of plantar pressure during walking and sports, integrating it directly into the insole of a shoe. This aspect constitutes a critical path to assess the gait of the subjects examined. Various gait variables during sport were obtained through these sensors, including plantar pressure (peak/average pressure), reaction force, and center of pressure (CoP) [82]. Foot pressure measurement is also essential in healthcare applications, clinical rehabilitation, and pedestrian navigation. In recent studies, nanotube-based pressure sensors/polydimethylsiloxane have been used to monitor it [83].

Integrated low-cost strain and pressure sensor systems were also used to measure wrist movements and obtained at low cost and with a simple production process. This time, the resistive bending strain sensor in the system was manufactured by polyimide sintering. In contrast, the resistive pressure sensor was implemented based on a composite structure of silver nanowires and expandable pressure sensors/polydimethylsiloxane microspheres with adjustable sensitivity and operation range. This system has shown great application potential in motion monitoring and intelligent human–machine interfaces [84].

Smart Insoles in Human Gait and Posture Analysis

Gait insoles are widely utilized for gait analysis, highlighting possible motion dysfunctions in healthy subjects or incorrect patterns in people with gait impairments. Indeed, real-time gait analysis represents a key factor in improving rehabilitation devices. Smart insoles have been studied for many years, producing increasingly simple and highly effective models, which may reduce the issue of uncomfortable wearable devices within the shoes. Foot pressure detection is fundamental in recording data on people's dynamic movement and posture [85] since the foot represents the first body point of contact with the ground and gives information on the world around [86]. Due to this, data records on foot pressure are essential to develop novel kinds of sensors (Figure 4).

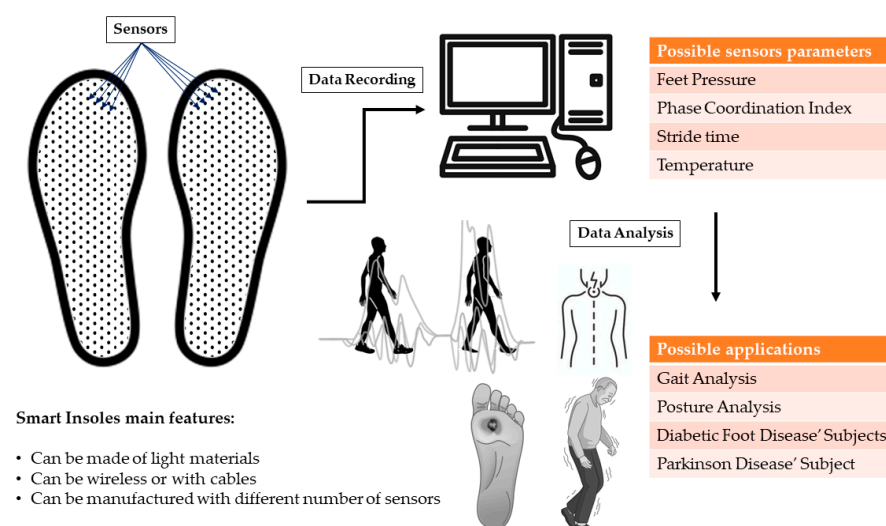


Figure 4. Insole outline of the recording and data analysis of smart insoles. Piezoresistive, photoelectric, 6-axis, pressure, and flex sensors were used in the reported studies. The number and position of sensor units changed concerning the author's decision.

Furthermore, the most relevant analyzed gait parameters are velocity, stride time, CoP, step count, and phase coordination index [87–91]. Ref. [86] developed a couple of insole models based on photoelectric sensing unit functioning, each composed of six-unit sensors capable of recording data on foot pressure, produced with cheap materials (elastic silicone). The authors proposed a test for moving from a natural standing to walking and returning to a standing position. The gait analysis outcomes were dependable, but the connecting cables represented the principal limit of such insoles to the device. Indeed, the cable could lead to impediment and discomfort during walking time, suggesting the need to produce a wireless model.

Ref. [86] presented a soft-material-based smart insole, which is light, durable, and wirelessly connected. The authors compared this proposed novel device to a commercial in-shoe cables-connected sensor to assess its performance. The tests performed simultaneously wearing both sensors and carried out at different walking velocities showed a full correlation between the two devices. The values recorded in this study led to comparable outcomes between the proposed wireless soft smart insole and the other cable-connected sensors. Ref. [92] produced a pair of insoles that may measure foot pressure, wireless connected to a smartphone or laptop, and controllable with a graphical user interface. This interface can show historical data obtained through measurements performed at separate times. Each insole was composed of sixteen piezoresistive self-sensors. One subject performed various movements wearing the insoles, such as standing, sitting, walking, ascending, descending, running, and jumping. Data collected in this study are consistent with other research performed through similar technologies.

Ref. [93] attempted to generate a self-powered insole to check the gait signals. Self-powered nanogenerators were applied for insoles working, and the devices were composed of hybrid multifilament materials. Two subjects were asked to walk on a treadmill at different self-determined velocities, simulating a limp walk. The highest value of nanogenerators' voltage outputs measured during walking was 41 V. It has also been possible to recognize differences in different speeds and limp walking performed during the experiment through the multiscale entropy analysis of stride intervals. Some other authors [94] proposed a smart insole to monitor other body postures, using four wireless Flexi force sensors and a flex sensor embedded within the insole, made of Polyvinyl Chloride. Results from this study, where four different body positions (tree, leaning forward, squat, and forward fold postures) were performed by a subject, showed that the feet pressure measured through the insoles changed during each body posture modification, growing on the first, fifth, and third metatarsals. In contrast, the leaning forward, squat, and forward fold postures were performed. Outcomes from this study suggest a potential application of these sensors in clinical areas.

The research on insole sensors is progressively growing, including uses in different subjects and clinical diseases. Many authors focused their research on people affected by diabetes foot, a complication of diabetes mellitus, which consists of developing ulcers on the distal segment of lower limbs, often leading to hospitalization of these patients [95]. For instance, in [96], a wireless low-cost piezoresistive device made of conductive rubber and carbon-based conductive fillers, composed of eight sensor units (including three units positioned on the forefoot, since it is the most common part of the foot in which ulcers grow) has been developed. Results based on a random forest classifier showed that these insoles could be potentially helpful in monitoring the data on foot pressure for preventing foot ulcers in diabetic patients by sending alerts to the mobile app interface. In [97], the authors proposed the design of an insole that can report foot pressure and temperature measurements and tried to investigate its feasibility. The authors reported positive findings, suggesting an application of this device in diabetic foot patients since data on foot pressure and temperature during the gait cycle can be collected and monitored, allowing the physician to detect early complications of foot modifications in diabetic patients.

Furthermore, Parkinson's disease is a condition of interest for studies on smart insoles because of shuffling and foot slight pitch angles that are common among this class of

patients. Related to this research field, ref. [98] shows the validation of gait values recorded through a commercial smart insole (FeetMe® insole, Paris, France). Recently, ref. [99] developed the Smart-Insole Dataset, a dataset in which healthy subjects, Parkinson's disease subjects, and elderly subjects' insoles data have been collected. The insole utilized for this research was the Motion SCIENCE insole, which has sixteen pressure sensor units and six-axis IMU sensors to record angular rate and acceleration data. The study asked subjects to perform different walking tests, such as the Walk Straight and Turn Test and a modified Timed Up and Go Test [99].

4.4. Force Sensors in Swimming

The action of the swimmer is the coordinated interaction between the trunk movements and upper and lower limbs [100]. The swimmers' capacity depends on the level of propulsive force applied during each stroke to allow the athletes to overcome the drag during the forward movement. Some studies affirm that 85–90% of the propulsive force is developed from the upper limbs, while the remainder is associated with the lower limbs [101,102]. In the cyclic form of locomotion, for example, in swimming, rowing, and kayaking, the intracycle velocity fluctuation is due to the combined effect of propulsive force and drag [103,104]. For these reasons, the study and the measure of propulsive force in swimmers play a crucial role in the athlete's functional assessment. The literature reports different studies about the direct or indirect methods to measure the propulsive force [105]; however, the standard practices proper to investigate the magnitude of the propulsive force in swimmers are tethered swimming, 3D video analysis, and the measured activity drag system [106].

In recent years, the applications of sports engineering have been geared toward developing differential pressure systems (sensor paddles) [105,107]. These systems base their functioning on measuring differential pressure through the two membranes situated respectively on the palm and the back of the paddles, measuring, in this way, the perpendicular component of the differential force acting between the palm and back of the hand. Subsequently, such a system can compute the dynamics parameters (force–time curves) of both hand swimmers' surface area via proper software. Furthermore, in some of these DAQ systems, such as the Kz system, the force data are integrated and synchronized (all the signals to be measured are acquired simultaneously) with an IMU that measures the athlete's kinematic parameters during the swim movement [107,108]. Today, the usage of these sensors in swimming is still limited because few studies confirm the reliability and validity, with a gold standard of the dynamic parameters provided by instrumented paddles. Furthermore, these sensors can estimate only the applied force on the swimmer's paddles (so the force impressed by hands only) without considering the swimmer's arm or forearm's contribution to the propulsion [109,110].

5. Kinematic Assessment of Movement Performance

The first application of a portable accelerometer in sports science was proposed in 1981 by the University of Wisconsin-Madison [111] to measure acceleration and deceleration on vertical axes to measure energetic expenditure. This device was rather bulky, weighing 400 g with a size of $14 \times 8 \times 4$ cm. Since 1990, these first accelerometer devices have increased diffusion despite the limitations due to relatively high costs, low reliability, and calibration difficulties compared to the provided advantages [112,113]. Starting from 2004, the introduction of the MEMS (Micro-electromechanical System) technology allowed for the integration of such mechanical systems, together with the control electronics, on the silicon of the electronic devices, allowing a very high reduction of their dimensions and relative price, increasing their diffusion in several application fields. Moreover, in the same years, the developments in wireless communication allowed for an exponential increase in the use of these devices in the sports field thanks to the implementation of light, which is unobtrusive without cables wired measurement systems.

The accelerometers present some limitations, mainly due to their positioning, movement artifacts, noise, and the selective recording of the movement of the specific part of the body to which they are connected. Today, the research focuses on developing multi-sensory devices applied to different body segments and combined with physiological measurements to provide more detailed information about physical activity and performance [112].

5.1. Inertial Measurement Unit—IMU

An IMU is a device manufactured using MEMS technology, and it is composed of more sensors, including an accelerometer, gyroscope, and magnetometer, working together to detect the acceleration rate and changes in rotational values, like pitch, roll, and yaw [114]. The features of IMUs can be identified from their Degree of Freedom (DOF), which is the number of values among axial accelerations that it can measure (e.g., a 10 DOF device that includes a tri-axial accelerometer, gyroscope, and magnetometer, plus an altimeter sensor is widely employed for drones' navigation control). Once fed into a microprocessor, it is possible to calculate the actual velocity and position using these data and proper integration procedures, given their respective initial values. Moreover, in some of the latest devices, an embedded high-performance processor enables the output of more detailed data based on the math of quaternions and Euler's angles [115] (Figure 5). These miniaturized inertial sensors are high-performance and can be considered a powerful alternative tool for measuring and analyzing sports movements [116–118].

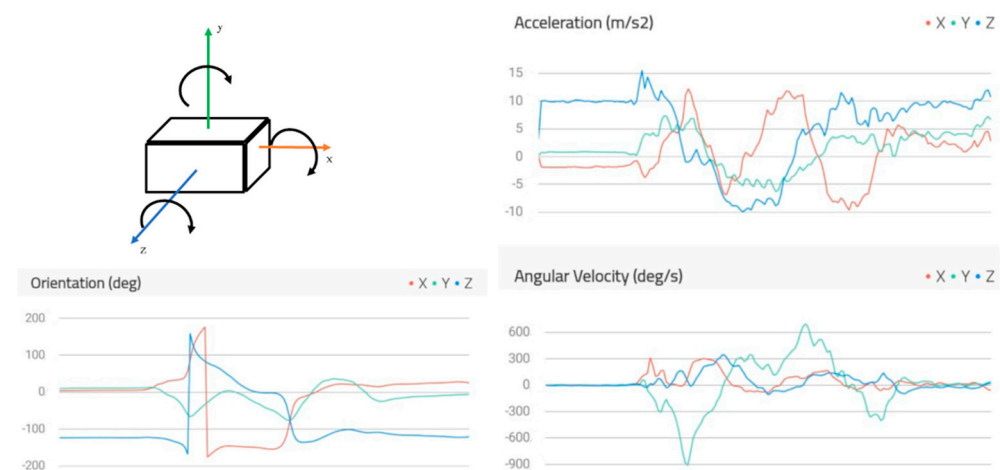


Figure 5. IMU is a device composed of accelerometers, magnetometers, and gyroscopes that can reach 3D information on acceleration and rotational motions. It is possible to access acceleration, angular velocity, and orientation graphs.

In particular, the IMU validity and reliability were researched on the wrist movement in the pitching phase in both baseball and cricket games and the punching in boxing, trajectory of the joints or velocity and acceleration in the snow sports and disability games, including wheelchair basketball, by comparing via Motion Capture System (MOCap, further explored in Section 8) [114,119–122]. Additionally, accelerometers are used to measure the agility, acceleration, and prediction of prevailing foot trajectory movement in team sports, including volleyball and football [123,124]. Additionally, the output of force sensors and the kinematic data obtained from IMUs were used to estimate jump height and ball impact timing in jump serve, block, and attack actions in volleyball coaching [125]. Another paper on long-distance running or triathlons reported measures on the modality of the foot support obtained by three-axis accelerometers placed on the back of the athlete near the lowest part of the spinal cord. By these sensors, they can assess the applied forces to the feet and study the cleat adjustment to determine acceleration magnitudes of the trunk [126].

On the other hand, the capture motion methodology cannot accurately provide fundamental quantities such as velocity and acceleration (hence, forces and torques) during high-speed motion, which is typical of many sports. Studies conducted on baseball illustrate that using IMUs is a valid method for quantifying the mechanism of generating the pitching ball's speed. IMU sensors were attached to the upper torso, arm, forearm, and hand segments. The movement of a baseball pitcher who was asked to throw to the target was measured with a combined Mocap and IMU system. The results detected by the quantitative analysis of the ball speed generation mechanism with the proposed method do not show inconsistencies with that performed by the Mocap system [127]. Another study compared the IMU (Xsens brand) with the Vicon optical MoCap system in the acquisition of walk, squat, and lateral lunge movements. The positioning of the joint heads in Xsens followed the trajectory of the Vicon data with a good approximation. Xsens can be a valuable alternative to the Vicon system, but it still has not produced clinically beneficial outcomes. Indeed, to collect meaningful data in the clinical study, it should be treated cautiously for a sizeable joint movement [128].

To date, considering that several coaches are used to assess the health and performance condition of an athlete by the simple observation of his motion and localization when this is foreclosed because the subject is swimming in water or his movements are too fast, like the pitching phase in cricket and baseball or the service in tennis, the use of an IMU device could help to overcome these difficulties. Indeed, IMUs, via IoT, make possible the measurement of several biomechanical parameters and functions of the shoulder, joints, and trunk, whose assessment could be helpful for the improvement of sports performances [41,129–131]. They represent a suitable alternative process of sports analysis that is quicker and simpler thanks to reducing the requirement of using multiple cameras or other extra devices.

Wearable inertial techniques have an essential role in paralympic sports analysis. In the analysis process of the disability or Paralympic sports, the device can be attached to the aid tool or facilities to reduce any limitation of movement for the athletes, such as placing the inertial sensors together with the localization system to the wheelchair as in rugby and wheelchair basketball to measure acceleration and speed [132,133].

In other measurements and studies of sports movements, the authors, by attaching surface electromyography device (sEMG) and IMU to the trunks of cross-country skiers [134], assessed trunk stability, propulsion generation, and balance maintenance. In other studies [135,136] related to wheelchair tennis, some IMUs were mounted around the axis of each wheel and on the camber bar of the wheelchair, respectively. Moreover, a target was located on the same bar to be used by the indoor localization system. Therefore, the system can detect the activity profiles by these sensors, particularly the covered distance, peak, and mean velocity. These are the parameters that, for this class of players, need to be taken into account to give them proper feedback and help them improve their body control.

As some articles on wheelchair basketball illustrate, besides the advantage of wearable inertial sensors or sEMG sensors and indoor tracking systems to analyze the techniques and performance of players with disabilities to understand the effect of the different levels of injuries on their performance. Another benefit of these sensors is to support the design of the aid tools or equipment to recognize their influence on athletes' satisfaction, such as the seat dump angles, backrest heights, and therapeutic cushion on the pressure index or gradient of the players [137–139]. These studies in paralympic sports require deeper care due to the special conditions of each athlete and the consequent impossibility of having broad statistics.

5.1.1. IMUs in Biomechanics, Health Monitoring, Injury Protection

Body motion study in physical activities can lead to understanding motor behavior, action, and reaction with the highest efficiency and injury prevention [140]. In [22,141], the utilized devices present meager weight, and their minimal size has made it possible to carry out several examples of unobtrusive wearable systems that have found interesting applications in monitoring the health or body motion in many sports activities avoiding

any imbalance posture for the player [142]. Recording health aspects on the training field or during matches rather than inside a lab can reduce the risk of health damage and improve awareness of the athlete's actual conditions. Moreover, the lower mass and weight of these wearable sensors are helpful in not breaking the players' attention and focus, allowing a more realistic and reliable measure [140,143]. For example, accelerometers can measure variables such as proper acceleration, which is useful for assessing a player's agility and predicting the prevailing foot activity in team sports, including volleyball and football [123,124,144]. Furthermore, IMU devices are widely used to assess the arm joints' acceleration in combat sports, such as karate, where they have been used to take measurements in the punching phase. In addition, in ball-throwing sports such as volleyball, baseball, and cricket, the IMUs are used to evaluate hip, elbow, and wrist angular acceleration in the smash and pitching phase [144–147].

Another application of wearable IMU sensors is the estimation of kinematic parameters strokes in racquet sports. A recent study [148] examined the kinematic parameters and their variability in the top-spin forehand stroke of seven elite table tennis players. The study utilized a wireless IMU placed on the hand of each subject. Researchers could use this technology to analyze and measure the movement characteristics and variations in the players' top-spin forehand technique.

In the selected articles, wearable sensors were used to measure health aspects in running sports such as football to monitor the health aspect of players via wearable health monitoring systems. These systems are equipped with multiple sensors attached to the skin surface to measure some health parameters, including heart rate and breath rate, blood pressure, and human movement, to obtain the list of health information of the players to increase health condition awareness and injury prediction and prevention. Finally, injury prediction is estimated by players' injury records and the collected data via GNSS systems, such as velocity, covered distance, and acceleration during a football season [22,141].

5.1.2. APDM by Opal

In the field of clinical applications, the Opal system by APDM (Ambulatory Parkinson's Disease Monitoring) Wearable Technologies Inc. is a popular generation of IMU systems in the clinical sports path due to capturing dynamic movements of the athletes or patients thanks to the accelerometer and stable gyroscope inside the device.

In [149], the reliability of the APDM device is controlled by the MoCap system as a gold standard by focusing on the lower extremity by measuring the angle of the hip, trunk, knee, and ankle during specific movements. It has been employed as a digital biomarker to collect, measure, and quantify biological aspects for athletes and patients during rehabilitation or exercise. For example, in [150,151], the Opal system was used in clinical trials of Parkinson's patients attached to their feet and lumbar region to record their daily physical activities. Opal is a digital biomarker that can collect, measure, and quantify biological aspects for athletes and patients during rehabilitation or exercise. In [150,151], Opal contains a magnetometer and a 3D accelerometer. The 3D gyroscope was used in clinical trials of Parkinson's patients attached to their feet and lumbar region to record their daily physical activities; the outcomes measured mobility and logistic regression employed in the process of health control.

In [100,152], to analyze the upper arm propulsion in crawl swimming sport, the upper limb kinematic was monitored to observe 3D of the wrist's trajectory via Opal and a stereo photogrammetric system and by collecting some variables such as velocity and arm coordination. In this research, the lightweight Opal device as the IMU system was built by five units, including a 3D accelerometer and gyroscope ($\pm 2000^\circ/\text{s}$), a 3D magnetometer (± 6 gauss), and 128 Hz.

5.1.3. IMU Installation into Sports Equipment

In the sports engineering field, IMU devices, thanks to their very small dimensions and weight, are broadly applied inside sports equipment because they can detect athletes'

motor behaviors with a limited impact on them [153]. In this category of performance analysis, the sports federations and the world of sports equipment manufacturers focused on the sensorization of both apparel and equipment that athletes utilize. For example, several studies used gyroscopes placed inside shoes that focus on the foot's position and the direction of applied forces to the foot or ankle. The main target of these studies is understanding the correct running style and enhancing the running formation and performance from both athletes' and shoe manufacturers' points of view. Among others, refs. [154,155] presented some results showing that the athlete can benefit from the proper foot orientation with better support surface in both locomotion and running with consequent improvements in injury prevention. Other studies that address the movement analysis of sprint running to improve performances focus on assessing the hip flexion and foot contact phase pattern by measurements obtained with six DoF IMUs placed on the dorsal surface of the foot or right above the ankle [156–158].

Moreover, in those sports that require an external object or equipment such as, for example, a stick in hockey, baseball, or golf, a racket in tennis or ping-pong, and a paddle in some water sports, the coaches can receive real-time feedback on kinematic aspects of the athletes' performance by mounting inside such equipment IMU sensors and proper acquisition systems able to analyze the action of the player and their skills during the use of the equipment itself [159–161]. For example, in [162,163], attaching an IMU device to a golf stick, a kayaking paddle, or an oar, the coach can attain some kinematic variables useful for the gesture assessment, such as angular velocity and acceleration for the golf stick by analyzing the swing while hitting the ball and stroke duration, symmetry, and frequency in kayaking or rowing.

In the e-Kayak system (shown in Figure 6), the IMU is placed on the boat on the rear of the seat, and it is synchronized with the force sensors mounted inside the shaft and footrest, respectively. Such a DAQ system can analyze the source of the propulsion (the force on the paddle) together with forward acceleration and roll and pitch angles of the skull (the effects of the paddling action on the boat), assessing, in this way, both the dynamic and kinematic performance of the paddler in driving the boat and how he is making propulsion. At the same time, by exploiting the measures of the forces applied by the legs on the footrest and the force signal on the paddle, the system can assess the effectiveness of the paddling technique.

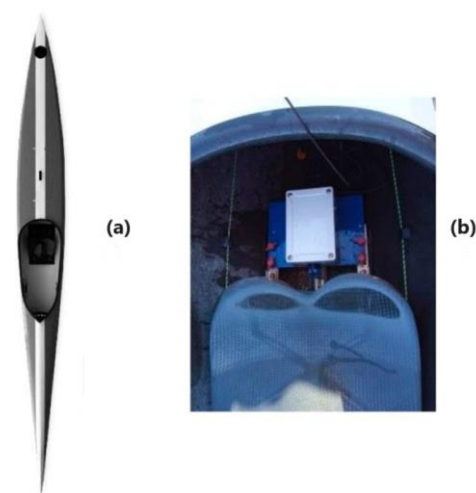


Figure 6. Bird view vision of the boat seat: (a) the waterproof primary node (E-Kayak system by APlab [17]) is installed (b) to acquire kinematic data from the IMU and GNSS.

In the new IMU technologies and abilities [164,165], waterproof sensors employ electrical connections in the apparel yarn by textile fabric electrodes. An interesting example is the application of this technique in a swim bralette top used to monitor some health aspects and physical activities [166]. This technology will oversee the limitation of IMU

underwater usage caused by the imbalance due to having a massive external device that increases the drag value, albeit with the restriction to having real-time monitoring of the performances due to the impossibility of carrying out radio transmissions in water.

IMU incorporating gyroscopes has been considered a practical alternative to 3D Optical MoCap systems for motion assessment in tennis. These two systems were compared in the evaluation of the angular velocity in the various tennis strokes. Two-hundred-forty angular velocity signals were recorded from different body segments and hit types (forehand, backhand, and serve) from two competitive and two novice players. The angular velocity of the IMU gyroscopes was compared with the same parameter obtained by the system, and the study concluded that IMU and MoCap showed comparable values. Therefore, IMUs are a valid alternative for evaluating angular velocity during tennis shots [167].

In another study, a six DOF IMU was integrated inside a basketball ball to measure players' dynamics during the practice and game exercises [168]. This study aimed to investigate the backspin rotational velocity and ball rotation axis during a shot. These factors are directly associated with the type of shot and the player's dribbling ability, which can be assessed by analyzing his dribbling frequency measured through acceleration.

5.2. Gym Physical Activity Tracking

Within the physical activity context, most wearable devices and sensors to assess performance are designed for aerobic and cardiorespiratory activity, monitoring and tracking different parameters such as the heart rate and the localization through GNSS. Gym physical activity, such as weightlifting, is less assessed if compared to walking, running, swimming, etc., probably because of its diversity and complexity [169].

Furthermore, many of these devices are based on machine learning models, such as random forests, decision trees, hidden Markov models, support vector machines, and naive Bayes classifiers. Thanks to the possibility of collecting more data from novel smartphones, fitness bands, and smartwatches, many studies have based their models on deep learning algorithms [170], which seems to be leading to interesting outcomes in this application field due to its capabilities in classifying large amounts of data.

Resistance exercise, generally performed within gyms, is not essential for athletes to enhance their performance; only strength improvement is possible [171]. It is also a non-pharmaceutical method that promotes a positive association in preventing age-related pathologies, such as sarcopenia and osteoporosis [172], representing a sports pillar and a clinical aid.

Due to the insufficient number of research in this field of exercise, probably caused by low funding compared to other exercise applications such as in endurance, several team sports, and clinical areas, not many devices have been developed to help practitioners of physical activity within the gym until now. Some authors tried to create sources to enhance gym training. For instance, ref. [173] developed an application to use during gym training, designed for a commercial smartwatch, to recognize the gym activity through which the repetitions performed with both bodyweight and additional weights exercises could be counted. Data collected from this app could record and diversify active (performing exercises) and passive (drinking, resting, walking) training time. The authors used a six-DOF IMU included within the smartwatch. A specific axis (for accelerometer and gyroscope) for each exercise has been selected and filtered, and a proper algorithm has been implemented to count every repetition for each of the performed activities. Results from this proposal have shown high accuracy, specificity, and sensitivity.

The authors in [169] attempted to develop a similar framework, which can recognize physical activity in a gym, utilizing an ECG and an accelerometer. They used a machine learning framework based on two hidden layers. Outcomes from this experiment have shown that the developed framework could classify nineteen different gym physical activities, calculate repetitions, and sets of every free weight exercise performed, and assess its intensity through the changes in heart rate and the calculations based on the repetition maximum principle. A further study investigated the potential of sensor-based gym physical

exercise recognition [174]. The authors' experiment model was based on a long short-term memory neural network with 100 Hz.

In [175], the acquired data was classified using an artificial neural network approach. The ANN algorithms are widely employed in classification problems because they can efficiently obtain a valuable outcome after exploiting proper training procedures over a large amount of data, even when handling large amounts of raw outputs from different sensors. In this case, three layers of a particular feed-forward ANN (i.e., Convolutional Neural Network—CNN) were used to classify data obtained from a forearm band sensor (Push) and a device utilized in several professional sports teams. Data used was already present in the dataset given by Push Inc. Authors have considered only the fifty most frequently performed exercises from such a dataset. Measurements were obtained from the accelerometer and the gyroscope within the sensor, with a sampling frequency of 200 Hz. Results showed good accuracy in the classification of the exercises considered, highlighting that sets with more repetitions seemed to be easier to classify if compared to groups with a low number of repetitions, maybe since subjects usually perform the movement worse on sets with few repetitions than on groups with a high number of repetitions.

In [176], the authors presented SensX, a special architecture for analyzing measurements obtained by different families of sensors to evaluate human motion chains. In such a study, the system was employed to test twenty athletes performing eight body weight exercises, wearing a central processor unit on the chest and four small IMU sensors, each one provided with an accelerometer, gyroscope, barometer, and magnetometer (ten DoF) placed on limbs. These sensor devices have been wirelessly connected by exploiting a Bluetooth BLE radio link (Figure 7).

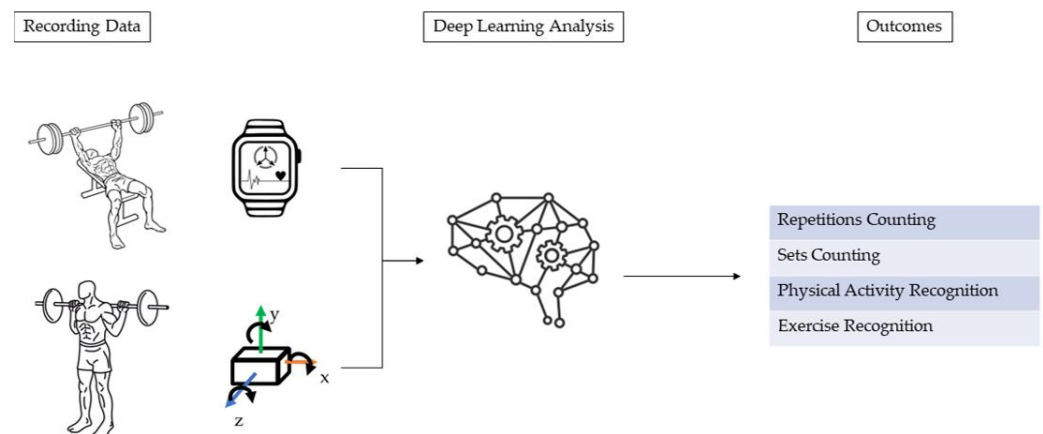


Figure 7. Possible gym wearable device illustration. Data are recorded via smartwatch or IMU and processed through deep learning analysis.

Later, the method of classification was based on naive Bayes classification. Average training data and cross-validation for all eight performed exercises resulted in more than 94%. Only the pushup exercise data was notably worse than the others, maybe because of the similar position of the mountain climber exercise or since the high effort caused by this complex exercise, as the initial hypothesis.

The paper [177] investigated a deep learning algorithm to recognize exercise and count the repetitions performed. In this experiment, the subjects were given two smartwatches worn on the wrist and ankle, respectively. They were asked to conduct ten complex full-body exercises (four bodyweight exercises, three with kettlebell, one with medicine ball, one with box, and one with pull-up bar), typical of CrossFit performances. The exploited deep learning algorithm was based on CNNs. The study employed a DAQ acquiring the output of an accelerometer, a gyroscope, and a magnetometer at a sampling rate of 100 Hz. The model proposed by the authors achieved excellent accuracy for exercise recognition and ± 1 error in repetition counting for 91% of the performed sets.

Research from [178] shows the production of a training tracking system called MiLift based on automatic segmentation. Through this system, which can be applied using several smartwatch models, it has been possible to recognize cardio, free-weight, and machine-based exercises, and count repetitions.

6. Localization Systems

Especially in team sports, a precise athlete's localization on the sports ground, in terms of position, velocity, and traveled distance, represents a paramount requirement in the game's tactic evaluation by the coaches and the assessment of the team's performance. A good estimation of the athlete's position allows the development of more accurate game strategies about any athlete's displacements on the ground and the possibility of conducting more precise studies of the performance model in individual sports. The localization process can concern the players' actions and the tracking of the leading moving object of the game such as, for example, the ball position.

For many years in track and field races, the photo finish, performed by manual visual analysis of a video stream, has represented the gold-standard method for analyzing the proper order of arrival of athletes, also providing the referee a time estimation to determine the athletes' position at the end of the race [179]. Currently, technology related to localization systems, exploiting different approaches, has obtained incredible progress in outdoor and indoor spaces. For example, in several sports, the acquisition and elaboration of video streams with computer vision methods help to detect and track the players' movements, as well as the ball trajectory, providing important information about the game dynamics and the relative tactical aspects [180,181] and support the competition judges in their decisions. Among others, in football, the tracing analysis through recorded images allows one to automatically detect the offside position of a player [182] or in volleyball or tennis, such systems, tracking the ball's position and trajectories, effectively support the referee in the "in/out" decisions.

The Global Navigation Satellite Systems (GNSS) and Local Position Systems (LPS) [183,184] can be identified for outdoor or indoor applications, respectively. The GNSS is widely known for its use in cars and smartphones for routing navigation systems. The same technology is commonly used today in professional athletic training and is often combined with the IMU-MEMS technology to improve the accuracy of the retrieved position. On the contrary, because of the satellite signal attenuation and multipath effect problems, GNSS cannot track indoor sports, and LPS is used for the athletes' localization operations. These latter systems employ short-range transmitters, each with a known precise location for estimating the target (ball or athlete) position through triangulation procedures.

The exploiting technologies for LPS are Ultra-wideband Band (UWB), Wi-Fi, Bluetooth, and Visible Light. These technologies are often used with IMU-MEMS sensors to improve the accuracy of the retrieved position.

6.1. Indoor Localization Systems

Indoor localization has recently shown increased interest because of the wide range of services it can provide by leveraging IoT technology and the ease of radio connectivity of mobile devices [179].

6.1.1. Wi-Fi Localization

The Wi-Fi system is primarily used to provide networking capabilities and connection to the internet to different devices. Initially, Wi-Fi presented a reception range of about 100 m, which has now increased to about 1 km (optimized for IoT services). Current smartphones and laptops widely support Wi-Fi and most portable devices, making it an ideal choice for indoor localization, even though the existing Wi-Fi networks are, to date, generally used for data communication (i.e., to maximize data throughput and network coverage) rather than localization purposes. Therefore, further algorithms are required to improve their localization feature. Additionally, interference in the ISM band

(i.e., the radio bands internationally reserved for specific Industrial, Scientific, and Medical applications) has been shown to affect localization accuracy [179]. Recent attempts have tried to resolve this problem by implementing deep learning-based Wi-Fi systems that achieve an acceptable accuracy of one to two meters [180,181].

6.1.2. Bluetooth Localization

Bluetooth is typically used to connect fixed or moving wireless devices within a specific space. The new BLE technology offers an improved data rate (24 Mbps) and coverage range (70–100 m) with higher energy efficiency than older versions. The protocol is designed explicitly for proximity detection and proximity-based services. The protocol allows a BLE-enabled device to transmit beacons or signals at periodic intervals [179,182].

One application of the Bluetooth localization system in basketball involves placing a wearable beacon with receivers on the court's border. Each player wears a small transmitting beacon to enable indoor localization while receivers positioned strategically around the court capture the beacon signals. By analyzing the signal strength or time delay at each receiver, approximate distances to the players can be calculated mathematically. For this technique to be effective, four receiving sites should be deployed around the court [185].

6.1.3. Ultra-Wideband Localization—UWB

UWB localization systems are the most recent indoor localization technologies. They consist of a radio-based communication technology for short-range use that makes use of very short radio frequency pulses (less than a nanosecond) [186], transmitted over a large bandwidth (>500 MHz) [179], to detect objects' location devices, as well as people, with excellent spatial resolution [187,188]. The main advantageous properties of UWB are good multipath resolution, a large channel capacity, and low energy consumption [186]. This feature makes it possible to obtain a centimeter-level accuracy. Therefore, it has become an essential solution for various applications. It is quickly becoming the leading technology in the indoor positioning market as measuring the variables consisting of velocity and acceleration, displacement estimation, and change of direction has recently been used in many studies to measure such parameters [117,118]. The UWB systems in recent years operated in many articles to measure motion tracking, especially in an indoor positioning system since there are errors and limitations to using other devices, including GNSS in indoor salons, and because UWB is immune to interference from other signals (due to the different electrical signal features) [179].

An exciting application of UWB technology occurred in hockey to determine the position of players on the court during a game or practice [186]. By exploiting this information, valuable characteristics have been derived, such as the covered distance and maximum reached speeds. In this case, the location system was combined with an IMU attached to the stick. Exploiting a sensor fusion process merging the data obtained by these two systems has created a broader and more detailed picture of what each player is doing at a specific time (Figure 8).

Another exciting study (conducted on American football players) compared the accuracy of the data obtained by UWB and GNSS systems. Such a study shows that the UWB localization system is a valuable solution to assess the players' position on the pitch with high precision, as well as in outdoor sports [189].

6.2. Outdoor Localization Systems

The leading technologies employed for localization in outdoor applications are based on GNSS or video analysis performed with multiple camera recording systems. The latter method is also widely used to support the referees in specific action evaluations. In addition, recent studies show that these proposed sensor fusion methods can give good precision in the order of meter level in outdoor positioning and centimeter level for indoor [190–192].

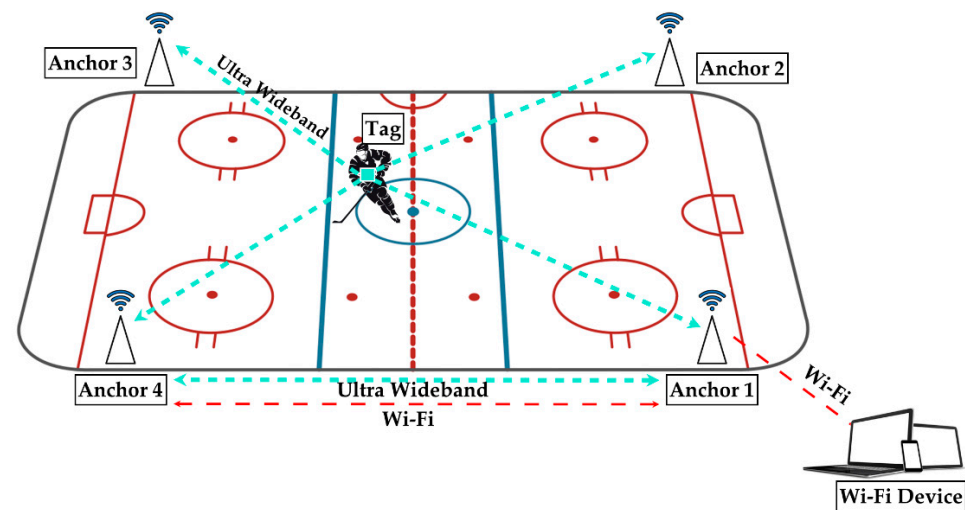


Figure 8. An example of a hockey UWB system for localization of a player in the field.

Wearable Navigation Systems

GNSS is widely used in sports to study the position, intensity, volume, and nature of athletes' movements, especially in sports where considerable activity occurs in an open environment. They are widely used, for example, in football and similar sports, to study the specificities of players' movements in various game roles or to quantify the kinematic variables of a canoe. Since the last decade, numerous studies have been conducted using GNSS on footballers. The analysis of the examined studies showed that athletes' competition loads, positions, movement patterns, heart rate, and speed data are the parameters mainly investigated [193–196].

Thus far, there are six satellite positioning systems (GNSS) in orbit: the Global Positioning System (GPS) by the United States, the Global Navigation Satellite System (GLONASS) by the Russian Federation, the European Galileo System by European Global Navigation Satellite Systems Agency, the Chinese BeiDou, the Indian Regional Navigation Satellite System (IRNSS) by India, and the Japanese Quasi-Zenith Satellite System (QZSS). The latest GNSS receivers are designed to support multi-constellation (most, if not all, of the available satellite constellations) and multi-frequency signals. These features aim to exploit satellite redundancy and, using some high-performant processing algorithms, fulfill localization error mitigation, allowing different sensor family integration. Moreover, thanks to the availability of several low-cost devices, and since these systems can retrieve the actual position with high reliability, accuracy, and continuity, the number of applications using GNSS is continuously growing [197,198].

However, these systems have limitations regarding kinematic analysis to detect vertical motions in any condition. For a better assessment of these movements, GNSS is often integrated using accelerometers or video analysis [199]. Studies to validate the use of a GNSS with an accelerometer unit (GNSS-Acc) were conducted to quantify the kinematic variables of the canoe. The analysis examined eight canoe and kayak sprint races, including 200 and 500 m distances [200]. A digital camera was positioned on the side for data collection, tracking the kayak's bow or canoe throughout each race. Simultaneously, a GNSS-Acc unit recorded relevant data such as the boat's position, speed, and acceleration. This comprehensive approach provided valuable insights into the performance and dynamics of the races. The GNSS-Acc unit data was analyzed using a self-developed routine. The agreement between the video and the GNSS-Acc analysis was measured, and no differences were found between the two methodologies, except for the time and speed at the first 50 m, thus suggesting an agreement between the analysis methods.

The GNSS-Acc unit is suitable for quickly and accurately measuring kinematic variables, mainly boat speed and ride rate. However, video analysis is required for a detailed examination of the paddling technique when a more comprehensive understanding is

desired [201]. Some systems that integrate GNSS, video analysis, and strain gauges are used to evaluate the efficiency of the interaction among the members of a flat-water sprint kayak crew [108]. In particular, the latest multi-channel wireless systems include a high-frequency GNSS receiver, an IMU, and two force channels for the paddle and foot brace. By synchronously integrating the values of all sensors, the microprocessor elaborates these and sends, in real time, the reconstructed parameters to a portable device via Bluetooth [24,103]. Another application of this technology was to analyze the football player performance model to evaluate valuable aspects such as physiological parameters and fatigue's role during matches (using GNSS Live 50 Hz) [202,203].

Furthermore, the recent developments in an emerging technology (Real-time Kinematics—RTK GNSS) made available a family of low-cost GNSS navigation receivers connected to an RTK base station, promising centimeters of performance in the location measurements [204,205]. This technology allows the GNSS receivers' incorporation of correction to increase the position accuracy of the receiver. Primarily, the receiver is under control remotely. The RTK base station is a stationary GNSS receiver of a known location that transmits correction data through radio or the internet. The RTK rover can achieve high-precision positioning with the help of an RTK base station within a 40 km radius. The RTK base station transmits correction data at a frequency of 1 Hz.

Another possibility is to determine the position of the RTK base station using a method called precise point positioning (PPP), which is based on an additional satellite phase of the bias information generated from a network of global reference stations [Networked Transport of RTCM (Radio Technical Commission for Maritime Services) via Internet Protocol—NTRIP] [206] (Figure 9).

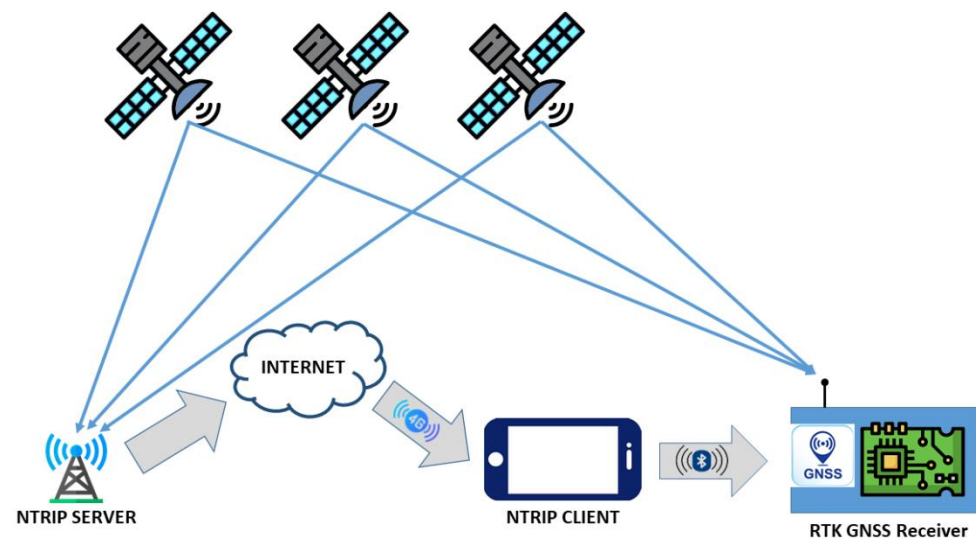


Figure 9. The RTK NTRIP system block scheme.

6.3. Position Measurement on the Playing Court by Video Analysis

Another process of player position and motion acquisition (tracking) in the court is made by video match analysis [207,208]. This computer-aided system takes place in individual and team sports analysis using video recordings of the match. An excellent example of this technology for football-specific performance analyses is TRACAB's tracking systems. In particular, the "Gen4" consists of two multi-camera units placed in two locations on either side of the halfway line. The "Gen5" comprises two stereo camera pairs on each side of the field and two monoculars behind the goal areas. Recent studies on twenty football players in the total distance traveled showed only trivial deviations compared to the reference system (Vicon MoCap system) [209].

Other studies in the football field compared the agreement of the movement demands data during a match (distance, average, and maximum speed) between an optical tracking

system and a GNSS device. The results of this study showed that the measurement variation between the two methods was minimal and promising [210].

7. Motion Capture Systems—MoCap

MoCap is the software (i.e. Boris FX Mocha Pro 2023, Xsens 3D MoCap—MVN Animate Systems-) process of recording and measuring the position and orientation of objects or people in 3D physical space. The studies were initially addressed to gait analysis in the field of life sciences and are currently widely employed in several application areas by visual effect studios, sports therapists, and neuroscientists, among others. Moreover, there is an increasing demand for ever faster, more sophisticated techniques to capture movement in various settings, from clinical to sports assessment. It is possible to identify four approaches to MoCap with the inertial sensors array technique (based on IMUs' arrays), optical systems, and markerless video techniques [211]. The number of reference points that must be identified with the manual marker positioning directly on each frame or by their software localization via the retroreflective devices in both optical technique or, in the markerless systems, their automatic retrieving will depend on the employed methods (2D or 3D) and the relative DoF required. Since the maximum value of recoverable DoF in a 2D analysis is equal to three, this requires a minimum of two known points on each segment to be analyzed. Conversely, for the 3D reconstruction of a rigid body, it is possible to specify six DoFs by identifying at least three non-collinear points.

7.1. Optical Motion Capture Systems

Optical MoCap systems exploit cameras to track the motion of reflective markers attached to specific locations of the subject's body. Two different approaches are commercially available: active and passive systems. The former is based on landmarks placed on the joint points implemented with powered markers made of light-emitting LEDs and daylight cameras. On the contrary, the latter only employs passive sensors traceable by infrared (IR) cameras. Some of them, namely deep optical MoCap marker-based (DeepMoCap), use multiple space-time aligned infrared depth sensors (IR-D) and retroreflective straps and patches (reflectors like passive markers) combined with fully convolutional neural networks (Figure 10).

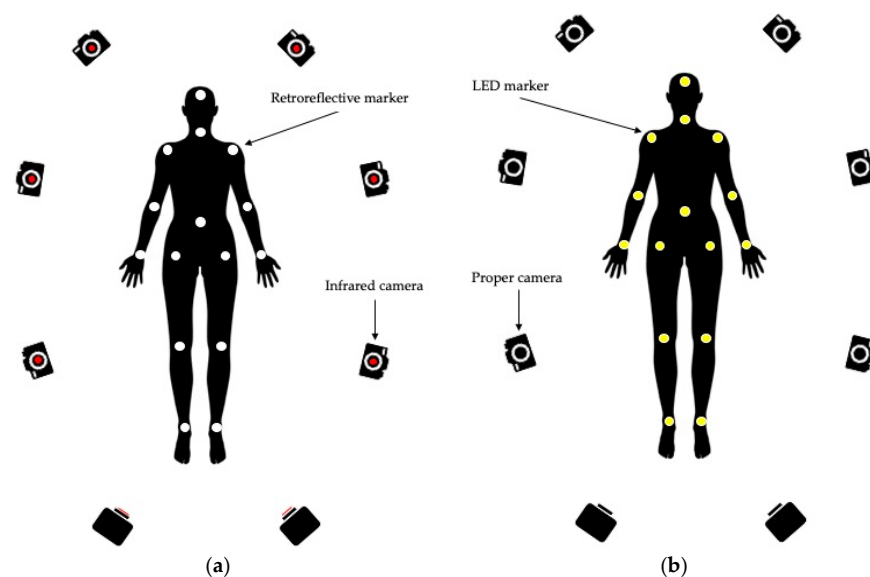


Figure 10. (a) In the active optical MoCap, infrared cameras recognize attached retroreflective markers on different body points to reproduce in motion analysis software; (b) in the passive optical MoCap, proper cameras recognize attached LED markers on different body points to reproduce in motion analysis software.

DeepMoCap is a MoCap system that utilizes depth images to locate and label reflectors automatically, enabling the reconstruction of 3D spaces. The proposed system, employing a model-based adaptation technique, efficiently captures only one person's movement from the extracted optical data. By placing reflectors and IR-D sensors around the subject, body movements are fully acquired, overcoming the limitations of a one-sided view, such as partial occlusions or damaged image data. The logic behind the use of reflectors is the exploitation of the intense reflections that cause the IR fluxes of the IR-D sensors, allowing them to be detected on depth images.

Spatial mapping and the alignment of the retrieved 2D points to 3D Cartesian coordinates using intrinsic and extrinsic depth data and IR-D camera parameters enable the frame-based 3D optical data extraction. DeepMoCap constitutes an alternative, low-cost, and flexible marker-based optical MoCap method that results in high-quality and robust MoCap outcomes. This process, called 2D reflector set estimation, replaces the manual marker labeling and tracking tasks required in traditional optical MoCap [212].

Active and Passive Optical Motion Capture Systems

Active systems embed IR cameras that capture the light reflected by markers attached to bodies or objects under investigation. The camera lens properly lightens these markers, and the acquired images are used to calculate the position of such points within a 3D space.

As an active optical system, Vicon is a reference tool for the calibration procedures of inertial and video markerless systems. This system works with cameras that detect proper markers worn by the players on various critical points of their bodies [213,214]. To assess the influence of different axes of rotation, namely the minimum inertia axis, shoulder-center of the mass axis, and shoulder–elbow axis, on the four distinct phases of the tennis serve (loading, cocking, acceleration, and follow through), a T40 Vicon eight-camera system was set up. This system enabled precise evaluation and analysis of the subject's movement during each serve phase. The global orthogonal reference system was chosen so that the x-axis pointed forward, the y-axis pointed vertically upward, and the z-axis pointed laterally to the right. Forty-three markers were applied on the joint points of each participant to the study, and five additional markers were placed on the racket. From the 3D position of the markers, the evolution of arm joint angles and joint center positions was achieved using custom MATLAB R2023b scripts [215]. Vicon cameras (Centennial, CO, USA) were also used in tennis to analyze the influence of racket kinematics on the ball topspin angular velocity and accuracy during the forehand groundstroke [216].

In [217], the analysis process of the soft-soled footwear, the kinematic variables for barefoot and footwear conditions were collected via the Vicon system by twelve cameras with twenty-nine markers. The operated markers were attached all around the body, such as the calcaneus, navicular, lateral aspect of the medial and lateral knee joint, iliac spines, and at C7 at the back of the neck. The markers' trajectory had been labeled and collected via Vicon Nexus 1.7 software. Due to the high accuracy of the Vicon system, ref. [218] used the equipment as a gold standard to compare the MoCap and kinematic measurement validity with an Artificial Intelligence (AI)-based image recognition detectable sensor [219,220].

The Vicon system required several body marker attachments, and data were sampled with Vicon Nexus software (v2.10, Oxford, UK). This study observed the DoF in the shoulder joint functional in standing still and abduction activities. In some recent studies, the Vicon system was used to evaluate the reliability of the running vertical jump test. In this case, twelve MX40+ Vicon cameras were used to capture movements synchronized with two Kistler force plates [221]. In another one, eight Vantage V5 Vicon cameras were used for 3D motion recordings to study the kinematic of initial step patterns for multidirectional acceleration in team and racquet sports [222]. In [223], it has been used in evaluating the functional torque force in the shoulder joint in overhead athletes with and without sub-acromion impingement.

Passive mocap embeds reflective markers positioned on objects tracked by high-speed or proper cameras. This method is popular in many fields and industries, such as sports analysis, biomechanics, and animation [224].

In football, passive mocap facilities are used to study players' kicking technique, agility, and body mechanics. Likewise, in golf, this technology aids in analyzing a golfer's swing dynamics and exploring the players' body pose in the backswing and downswing phases [225]. Gymnastics is another sport that benefits from passive mocap by accurately capturing intricate routines to help balance and the fluidity of the movements [226].

OptiTrack has the potential to be set up as a passive optical mocap method, offering the capability to capture intricate movements in diverse sporting scenarios. OptiTrack systems prove particularly well-suited for sports biomechanics research [227]. Whether scrutinizing the finesse of a football player's footwork or dissecting the nuances of a gymnast's routine, OptiTrack's passive optical mocap technology provides robust and detailed data crucial for elevating athletic performance [228,229].

7.2. Wireless System for Motion Capture Analysis

Movit System G1 by Captiks is a valid example of several acquisition systems suited for MoCap and motion analysis that are selected to be discussed in this review. The Movit inertial sensors can be applied to the subjects' joints using elastic bands or directly to their clothes. In [230], the system, composed of seven Movit units, has been validated in some gait and posture analysis tests using the optoelectronic system Vicon. The Movit System has been employed in some studies to identify motor impairment in patients scanning [231].

Moreover, an interesting application of such a system, as described in [232], was its employment with patients at an early stage of pathology. In this case, the kinematic data obtained by the system were successfully used to evaluate, in early Parkinson's untreated patients, those motor features regularly used to highlight the specific Parkinson impairments and assign them a proper clinical score [233].

Furthermore, another rehabilitation study assessed the efficacy of the therapy by analyzing upper limb motion in specific tests and examining the motor strategy exploited by the subject during the trial. In this case, the sensors were applied to the upper limbs, trunk, and head [234]. In particular, the subjects were asked to perform the test with the dominant and non-dominant arms at their own pace and velocity.

7.3. Markerless Video Analysis

While the markerless and deep learning application on video analysis does not rely on wearable tools or markers, its validation is closely related to wearable technologies, and, most probably, many studies and software in this area will be designed in the future. Thus, the authors decided to explain this technique briefly. Markerless video analysis technology presents the main advantage of performing these measurements automatically and unobtrusively and, particularly if markerless, without any impediment to the free movement of the subject. By analyzing image sequences, the system estimates an item's pose (i.e., position and orientation) inside a scene. Through the identification of specific markers in each of them, it can track their displacement over time. In the case of human motion analysis, this operation could often be somewhat complex to fulfill due to the conformation of the human body (e.g., several self-occluding parts, many articulations, etc.). In some instances, especially among biomechanics studies, when assessing movements that are considered to occur primarily in the sagittal plane, such as the cases of walking and sprint running, the use of one camera only, together with an analysis performed with relatively simple 2D body models, can be helpfully set up [235–237].

Conversely, when the movement under study occurs in multiple planes (e.g., when analyzing the shoulder movements in the different volleyball spiking), multi-camera systems and 3D analysis are required. In 3D analysis, the structure of the human body is often simplified as a collection, with growing complexity, of joint points (called Key Points) and relative segments linked by frictionless rotational joints. Initially, these Key Points were

identified by manually annotating the images; later, this was fulfilled using marker-based optical trackers and IR cameras [238,239]. This operation is implemented on computer vision tasks, using sophisticated human 3D body models and the so-called pose estimation procedures. These are based on AI and machine learning algorithms that use sizeable human motion datasets and can efficiently estimate joint points and poses from images of people. This technique has several applications in various fields, including healthcare, gaming, augmented reality, and sports. The output data of these analyses is often combined with kinematic and kinetic data, allowing the calculation, through inverse dynamics analysis, of joint moments and powers [240,241] for a deeper, helpful analysis to characterize joint torque profiles in case of rehabilitation or recovery. Machine learning is pivotal in the [242], facilitating the extraction and assessment of high-level features for characterizing human activities. It enables the successful extraction of these features from CSL-SHARE and UniMiB SHAR datasets, supporting cross-dataset activity classification. [242] highlights machine learning's role in addressing challenges like imbalanced and few-shot learning scenarios, showcasing promising outcomes.

Markerless methods were used to measure the 3D movements of the tennis racket using a camera. The technique utilized in this study involves capturing a silhouette of the racket by using a camera with an unknown relative pose. A candidate relative pose is then employed to assess the consistency between the shape and a set of racquet silhouettes captured using a fully calibrated camera. The level of inconsistency is quantified as a cost function associated with the candidate's relative pose. This approach can estimate the camera's pose close to the racket silhouette. By adjusting the pose parameters, it is possible to make an accurate estimate of the actual pose of the racket. A proper validation scheme was developed to compare exposure estimates with data obtained using the camera's calibration software. Therefore, this system seems to be a valuable method for measuring the movements of a tennis racket in actual playing conditions [243].

The Kinect MoCap method is a markerless video analysis system initially produced by Microsoft in 2010. Kinect sensors provide new and improved capabilities for motion detection and 3D reconstruction. Its software automatically scans the scene and carries out the segment and players' tracking employing depth cameras and laser scanners [244]. It has IR detectors and emitters to capture human physical activities. The critical components of Microsoft Kinect sensors are RGB cameras, IR depth sensors, and multiple microphone arrays. Kinect v2 has better features than the previous version, such as better resolution, image recognition, and broader area view. A further significant part is that Kinect v2 has better skeletal joint tracking and can capture twenty-six joints, while Kinect v1 can capture twenty joints [245]. This system was initially developed within the scope of the gaming and entertainment fields, but it later proved highly interesting in sports, clinical, and rehabilitation applications [246–248]. Kinect sensors also introduce many features that allow for more accurate research on the movement of the human body and its gestures. Through its use, the coaches can access real-time data, compare the motion data, and understand the player's motion in an animation reproduction [249]. The central part of the Kinect (Microsoft released Xbox360 game console peripherals, Kinect) software is the skeleton recognition, joint positioning, adaptation to human movement, and body-tracking capabilities of two people simultaneously (Figure 11).

The depth camera can provide helpful support to the analysis by avoiding background parameters disturbing the process of participants' motion recording [250]. Microsoft Kinect is a non-invasive sensor essential for medical diagnostic and therapeutic purposes and a valuable tool for gait abnormalities, postural disturbance analysis, and physiotherapy. It can also help monitor the progress of patients undergoing rehabilitation.

In sports, to create a dataset of fencer movement and action during the fencing competition, the Kinect software system was used to reach real-time feedback for the speed performance and slow-motion fencer's body slow motion, motion recordings, and analysis of body and sword movements in both offensive and defensive modes [245]. Likewise, in the clinical setting, the Kinect is used to analyze the joint for natural human

actions and pieces of training, such as single-leg squats. Some facilities of Kinect in clinical analysis include calculating the net trajectory angle and estimating the best-fit line in squat movement in lateral or medial movements [251]. A recent study evaluated the validity of a markerless 3D full-body motion tracking method based on a single RGB-D camera compared to a gold-standard marker-based system. Twenty-three children and young adults performing different movements using a Microsoft Azure Kinect RGB-D camera version 1.1.2 and multi-camera Vicon Nexus 2.10 system simultaneously have been recorded. It seems to have a satisfactory accuracy most of the time and is close to the gold-standard system but not indicated for clinical motion analysis [252].

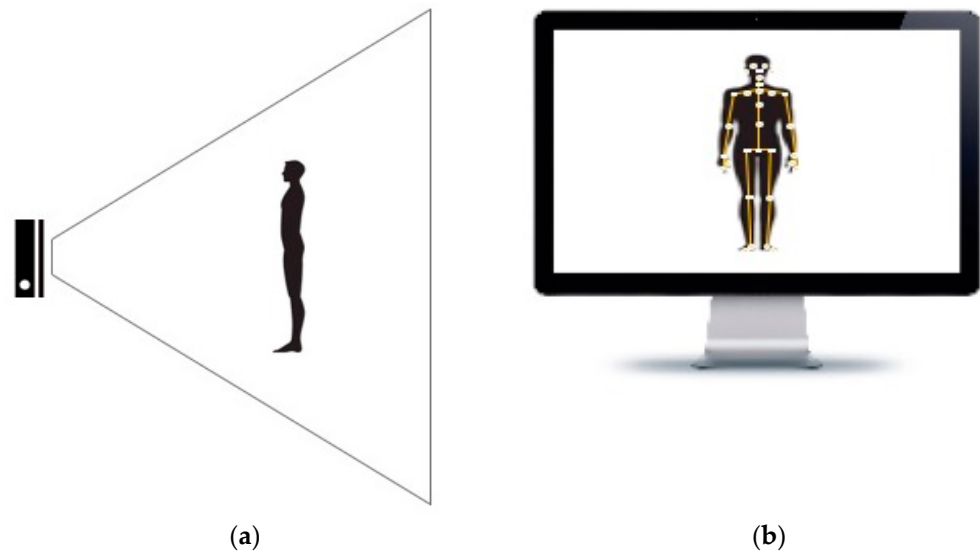


Figure 11. In the Kinect System, depth cameras and laser scanners automatically recognize body segments (a) to be reproduced in motion analysis software (b).

7.4. Deep Learning Application on Video Analysis

Aiming to supply the coaches with even more effective and reliable tools, computer vision-based systems for sports analysis are being developed to provide effective means to collect characteristic data related to sports and draw meaningful insights from data recorded during sports performance. These video recordings are often difficult to analyze and could hide, especially in team sports, valuable information on athletes' positions, tactics, strengths, and weaknesses of each team member. Also, in individual sports, player tracking is a crucial prerequisite for realizing advanced analytics to accurately evaluate each of them and improve performance, which might not be possible using traditional training methods. Ideally, the coach can now access a complete record of the athlete's parameters many times per second during an entire training session or actual athletic gesture [253].

However, just like other fields of application, even when considering the sports field, it is necessary to deal with many of the typical problems of computer vision [254]. In case one must deal with the real-time monitoring of multiple athletes, even the video of a sporting event includes particularly demanding tasks due to the continuous movement of the players that can generate partial or total occlusions from the point of view of the cameras, confusion, and misunderstandings due to similar appearance, etc. Furthermore, the amount of data to be processed is so large that automated tools must be developed to face and solve the task. This requirement explains the recent increase in AI and deep learning algorithms to perform various activities such as athlete tracking, eventual ball tracking [255], player or ball trajectory prediction, action detection and recognition [256,257], tactical analysis [258], group activity [259], advanced semantic understanding [260,261], etc. Recent developments in sports video analysis [262], using the most modern AI techniques, have significantly improved, providing advanced information, such as complex and detailed analyses in individual and team sports such as football, basketball, volleyball, etc. [263]. In team

sports that involve intense physical contact, which can include blocks and landings, such as rugby and American football, the tracking, detection, and objective recognition of an athlete's movements and actions during match play can be viewed as an opportunity to understand the etiology of the injury by improving the understanding of how the injury occurs. Head injuries are a significant concern for these sports. Head injury prevention requires a systemic approach, which implies machine vision analysis that can be used to assess the risk of these contacts, which helps coaches advance on how to train the tackle [264].

As the most widely available data source in sports, kinematic data are an intermediate representation of the performance of the athlete's technical and tactical gestures [265]. In the context of sports trajectory data, the goal was mainly to model trajectories to generate metrics for an athlete and team player evaluation or to make predictions and generate trajectories for game simulations. While in some sports, only ball and player tracking is sufficient to perform a helpful analysis, in other sports, such as rowing, tennis, hockey, etc., it may require additional detections, which include the object, paddle, racket, stick, etc., that the athlete is holding [266].

The extensive applications of these performance detection systems in the broadcasting sector have led to numerous commercial video analysis and tracking systems that can be effectively used in several sports. The characteristics analyzed by these systems include both individual performance and group behavior. Recognition of group activity aims to understand each participant's action and how they interact in a group context. Tracking group activity in sports has several practical applications, such as evaluating team strategy [267].

The techniques used in commercial broadcasting analysis systems range from those that rely on the direct intervention of a human operator acting on the screen on a calibrated image of the camera up to the most modern automatic video analysis systems [268].

Regarding the latter, recently, two systems have established themselves for their performance, STATS SportVU and ChyronHego TRACAB, standing out among the best technologies available for monitoring the performance of athletes in different sports. Their primary application area is to track athletes to analyze their performance and assist coaches in training. SportVU is a computer vision technology that provides real-time optical tracking in various sports; it collects data, tracking every player to provide tactical match analysis and highlight performance deviations to reduce in-game injuries. It is a camera system that collects data at 25 fps. The system uses two clusters of three HD cameras for basketball and football to provide statistics such as real-time player and ball positioning through software and statistical algorithms [253].

The ChyronHego TRACAB optical sports tracking GEN5 system is a scalable and distributed camera system that has successfully integrated into over three hundred stadiums, and it is used by football in UEFA (Union of European Football Associations), FIFA (Fédération Internationale de Football Association) international tournaments, and several national leagues. This system can guide teams to make crucial decisions that improve their athlete's fitness level, reduce injuries, and learn more about tactical choices, enhancing the chances of success. Dedicated static cameras are combined to deliver an analysis system capable of calculating player and ball position with only three frames of delay. This data is instantly available for on-the-fly video analysis and compelling graphical visualizations. The TRACAB system utilizes super-HD cameras and proprietary image processing technology to provide real-time tracking of all moving objects on the playing field. This advanced system enables accurate and comprehensive monitoring of players and other objects during sporting events [267].

The TRACAB system employs a distributed camera architecture, including two stereo pairs on each side of the field and two monocular systems behind the goal areas. This configuration ensures comprehensive coverage of the playing field and allows for accurate tracking and analysis of events from multiple perspectives. All the actions are seen from four angles, and the ball and players can be tracked efficiently. The software analyzes every image to extract the 3D positions of the center of gravity of all objects for each object on the

playing field thirty times a second, reaching an accuracy of about eight centimeters. This system was validated using the Vicon system [269].

8. Sensor Fusion

Sensor fusion is the combination of the information obtained by acquiring data from more synchronized sensors (of the same or different types) located in the same system (body area network or wider one). In particular, it can be defined as a suitable integration of the data acquired from more sensors that can produce more accurate results, which is not otherwise possible to obtain with the same obtained data but is singularly analyzed [270]. It is increasingly widespread and discussed nowadays. This fact results from two motivations: the easy availability of more measured sensor data and the requirement for a deep and accurate analysis of complex systems. Indeed, thanks to IoT, there is a wide and easy availability of many low-cost, unobtrusive, and wirelessly interconnected sensors. On the other hand, due to the vast number of features involved in complex systems, such as, for example, human movements, only one signal acquisition can rarely provide a reliable and complete analysis of them.

Sensor fusion has emerged as a rapidly advancing field of research, driven by the growing availability of various sensors. As the number of sensors placed, for example, in a BAN, still increases and, consequently, the throughput of the acquired data, a strong need exists to manage and fuse this large amount of information effectively to facilitate the human perception, understanding, and evaluation of each measured parameter. Indeed, too much data could make its comprehension very difficult, if not even impossible.

On the contrary, combining and integrating these data allows for new capabilities in myriads of areas.

Information obtained throughout the fusion process is more abstract than the original individual input dataset. In addition, this feature allows higher resolution of the data compared to that of each initial source of information. We expect the probability of the data to increase after the fusion process, increasing the confidence rate of the data in use. The system's reliability is also improved by combining synchronously acquired data in case of sensor error or failure. Moreover, if the source data is noisy or presents errors, a proper fusion algorithm could try to reduce or eliminate them.

Furthermore, the accuracy can be improved by the parallel processing of information from multiple sensors of different natures. Indeed, if individual sensors only provide information independent of the other sensors, once they are brought into a suitable space, this will give a broad view of the whole. Consequently, the accuracy would improve if the data acquired is consistent and redundant.

Finally, the several datasets must be aligned and properly converted in a common space for the fusion to occur effectively. Moreover, it is very important to avoid possible calibration errors of such sensors to make the fusion procedure possible.

The algorithms exploited for sensor fusion are in probability theory, classification methods, and artificial intelligence [271]. Among the others, the main ones used are the Extended Kalman Filter, Gradient Descent Method, Explicit Complementary Filter (ECF), Gauss–Newton Algorithm (GNCF and GNKF), Bayesian Inference Technique, Support Vector Machine, Particle filter (Sequential Monte Carlo methods), Dempster–Shafer Theory of Evidence, Artificial Neural Networks, and Fuzzy Logic. The individuation of the more suitable depends on the requested level of fusion [272,273].

One example of sensor fusion application involves combining positioning data with inertial sensor data to monitor an athlete's movements precisely. Proposed in a recent study to overcome the problems caused by non-Gaussian noise and sharp direction changes, this solution has proved to be very satisfactory [274].

In kayaking, a system based on IMUs consisting of seventeen miniature IMUs with nine DoFs was used to track the kayaker's motion. They use the gradient descent algorithm for data fusion, assessing his paddling technique and reconstructing the motion information [201]. A further paper by the same authors deals with a machine learning

algorithm that divides the stroke cycle into the propulsion and recovery phases and obtains a quantitative kinematic analysis together with assessing the intra-limb joint symmetry in the paddling action [275].

The application of wireless sensor fusion for heart rate and motion acceleration in individual competitive sports has been shown in recent studies to be much more precise and accurate than traditional methods [276]. However, as different applications require different numbers and types of sensors, it is difficult to define an overarching optimal number of sensors for any given system.

On this topic, the SmartSki prototype, proposed by [277], has been designed employing IoT technologies to connect ski equipment and body sensors. Such a system can measure the force applied to the skis and their corresponding bend exploiting some force and bend sensors wired connection to a central unit stored in a backpack worn by the skier and placed in different positions on each of the skis with the aim of assesses the distribution of the force applied from the skier to each ski. In particular, the force sensors have been placed in the left and right positions at each ski's toe and heel bindings, respectively, while the bend ones have been positioned in the front and rear skies sections. In addition, the system hosts a six DoF IMU attached to the skier's torso and a high-definition camera mounted on his helmet. All the sensor signals are acquired at a sampling rate of 100 Hz and synchronized using a cRIO board (by National Instruments) (Figure 12). By processing some of the raw acquired signals together, SmartSki can obtain, among other parameters, the total dynamic load, the tilt, and edge balance, which are not directly measurable by any single sensor. A proper sensor fusion algorithm, combining accelerometer data with those acquired by the skis' load sensors, can detect their carving motion more reliably. Furthermore, the images recorded with the helmet camera can also be exploited to assess the skier's technique. They could be integrated with the outputs of other sensors to improve the reliability of the evaluation.

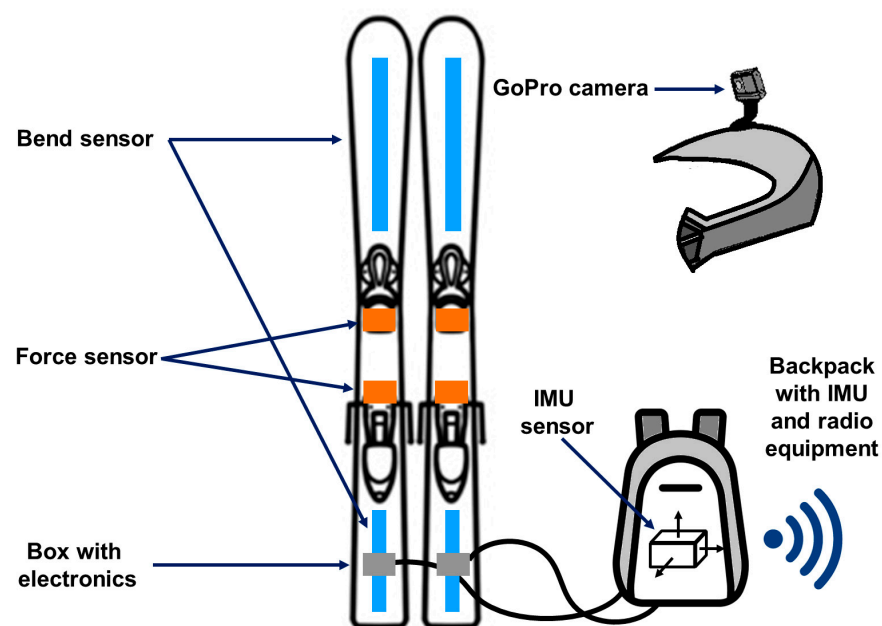


Figure 12. SmartSki system represents force and bend measurements on skis. It includes sensors, electronics, an IMU device, and a backpack for hosting the measurement devices. cRio system receives 100 Hz sensor signals.

Ref. [278] presents a system that has been developed for the identification of basketball shooting postures exploiting deep learning-based algorithms. This system consists of two IMU sensors placed on the main force hand and foot, respectively (e.g., right hand and left foot for right-hand players). The sensors acquire kinematic data (linear acceleration and angular velocity) at a sample rate of 100 Hz, and they are wirelessly connected to a Personal Computer. As reported in the paper, not all basketball shooting postures can be identified

by the movement of the main force hand. Indeed, for composite shooting postures such as the stop-jump shot, the kinematic data acquired by the IMU of such an arm cannot describe the features of the movement. Thus, as the first step, the algorithm proposed by the authors performs a merge of the kinematic data obtained by hand and foot sensors to obtain the input to feed the designed deep learning posture identification algorithm.

9. Conclusions

This review highlights how emergent technologies, such as wearable miniaturized sensors or video analysis, can significantly affect monitoring physical and physiological responses and kinematic aspects during practice as imperative for performance enhancement and injury risk reduction. The demand for integrated sensors that are comfortable, wearable, and user friendly underscores a strong need for a seamless monitoring experience. Currently, advancements in technology have allowed, at a meager cost, the reduction of the dimensions and the weight of such sensor circuits that, together with their easy radio interconnection capability, enabled the possibility to instrument much apparel or sports equipment able to monitor, in an increasingly less invasive way, the external and internal load in training and official competitions, also giving an always more accurate sports performance model opening to new dimensions in training methods and sports analysis. On the contrary, too much data availability can be difficult to understand if not properly organized and coordinated. In any case, assessing this technology's reliability and accuracy involves scrutinizing data from experiments and utilizing gold-standard procedures for their validation. In addition, the continuing push in the search for new and better-performing technological solutions for increasingly detailed analysis of human movement will surely have important fallouts in the clinical field. Consequently, the knowledge gained will contribute to developing even more precise and reliable health and personal profiles, enhance preventive measures, and facilitate remote control over time.

From this perspective, the next challenge of technological advancements in sports and the clinical field will surely be the development of new strategies and algorithms that can merge the information obtained from a vast amount of measured data. In this field, proper sensor fusion procedures and AI-based algorithms must be developed to exploit this amount of easily available sensors to monitor biometric and physiological parameters.

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