Biomimetic Intelligence and Robotics 3 (2023) 100097

Contents lists available at ScienceDirect

Biomimetic Intelligence and Robotics

journal homepage: www.elsevier.com/locate/birob

Review

IMU-based motion capture system for rehabilitation applications: A systematic review

Chenyu Gu[1], Weicong Lin[1], Xinyi He, Lei Zhang, Mingming Zhang*

Shenzhen Key Laboratory of Smart Healthcare Engineering, Department of Biomedical Engineering, Southern University of Science and Technology, Shenzhen 518055, China

ARTICLE INFO

Article history:
Received 31 October 2022
Revised 7 January 2023
Accepted 11 February 2023
Available online 27 February 2023

Keywords:
Motion capture system
Rehabilitation
Inertial measurement unit
Systematic review

ABSTRACT

In recent years, the use of inertial measurement unit (IMU)-based motion capture (Mocap) systems in rehabilitation has grown significantly. This paper aimed to provide an overview of current IMU-based Mocap system designs in the field of rehabilitation, explore the specific applications and implementation of these systems, and discuss potential future developments considering sensor limitations. For this review, a systematic literature search was conducted using Scopus, IEEE Xplore, PubMed, and Web of Science from 2013 to 2022. A total of 65 studies were included and analyzed based on their rehabilitation application, target population, and system deployment and measurement. The proportion of rehabilitation assessment, training, and both were 82%, 12%, and 6% respectively. The results showed that primary focus of the studies was stroke that was one of the most commonly studied pathological disease. Additionally, general rehabilitation without targeting a specific pathology was also examined widely, with a particular emphasis on gait analysis. The most common sensor configuration for gait analysis was two IMUs measuring spatiotemporal parameters of the lower limb. However, the lack of training applications and upper limb studies could be attributed to the limited battery life and sensor drift. To address this issue, the use of low-power chips and low-consumption transmission pathways was a potential way to extend usage time for long-term training. Furthermore, we suggest the development of a highly integrated multi-modal system with sensor fusion.

1. Introduction

Rehabilitation is an important disease treatment for people of all ages and patients. According to Cieza et al. [1], almost 2.41 billion individuals benefited from rehabilitation for their health conditions in 2019; this number has increased by 63% from 1990 to 2019. Furthermore, with the intensification of population aging and the increase in human life expectancy, people in their 60 s suffering from chronic diseases share a greater possibility of injury and body bone fracture. Rehabilitation therapy can help regain or improve motion function and enhance their quality of life by diagnosing diseases and providing practical therapies. Thus, rehabilitation plays an increasingly important role in human life.

Whereas the expanding rehabilitation need is largely unmet, data show that in some countries, more than half of the people in need, especially those from the lower class, do not receive sufficient rehabilitation care. Due to multiple factors such as the lack of medical funding, rehabilitation resources, and experienced doctors as well as the relatively expensive costs, people with rehabilitation needs are facing severe difficulties. Thus, the World Health Organization has launched the Rehabilitation 2030 initiative to address this rapidly enlarging unmet rehabilitation demand and relieve the difficulty among these people [2].

Traditionally, rehabilitation mainly depends on the treatment given by the rehabilitation therapist. This method is not only time-consuming and laborious but also lacks quantitative and systematic standards. Recently, an increasing number of rehabilitation equipment have been used in the field of rehabilitation, which has improved treatment efficiency and achieved electronic rehabilitation. Therefore, to improve the quality of rehabilitation and civilian rehabilitation for the public, new rehabilitation needs to combine traditional rehabilitation with advanced equipment.

1.1. Motion capture in rehabilitation

Motion capture (Mocap) system is an emerging technology that can capture human motion using inertial measurement unit (IMU) sensors or optical cameras. It can be used for motion disability that affects the activity of daily living due to limitation in range of motion (RoM) and abnormal neural control [3]. A goniometer is traditionally used for joint angle measurement. However, the combination of different segment motions renders

* Corresponding author.
E-mail address: zhangmm@sustech.edu.cn (M. Zhang).

[1] These authors contributed equally to this work.

https://doi.org/10.1016/j.birob.2023.100097

complex measurements difficult considering alignment with the joint center.

The Mocap system shows advantages in measuring and decreasing the misalignment. Compared with the traditional supervision and evaluation conducted by the rehabilitation physician during the rehabilitation process, the Mocap system gives accurate joint angle sequences, visualizes the patient's motion, allows remote rehabilitation, and provides big databases for further data processing [4].

Mocap systems can be classified into optical motion capture (OMC), inertia-based, electromyography-based, and fusion-based systems [5].

Among the Mocap techniques, the marker-based optical Mocap systems exhibit high accuracy in the measurement of human motion kinematics and are always regarded as the gold standard when compared with other Mocap systems. Whereas the drawback of the optical Mocap system is obvious, it needs sophisticated calibration and requires sufficient illumination backgrounds. Furthermore, an optical Mocap system is space-limited, typically expensive, and not easy to deploy (always needs markers). The imaging effect is also easily affected by the different reflective objects and occlusion.

At present, novel low-cost micro-electro-mechanical system (MEMS) inertial sensors have been widely used in Mocap as a cost-effective system. The inertial sensor usually consists of an accelerometer, gyroscope, magnetometer, and signal transmission chip. The IMUs have several advantages, such as low cost, customization, flexible application, and comfort in wearing.

There are already some successfully commercialized inertial Mocap systems, e.g., Noitom (NOITOM LTD.) and Xsens (Xsens Technologies B.V.). Many rehabilitation centers have used commercial off-the-shelf products and special applications for motion and gait analyses [6]. Study shows that wearable inertial sensor has been increasingly used in medical application. In rehabilitation, an IMU system with long battery life can be effective in monitoring human motion in daily environments, providing supplementary information to laboratory tests [7]. However, the gold standard OMC can be difficult to use for continuous monitoring due to variations in illumination and the possibility of occlusion. IMU-based Mocap systems are portable and easy to deploy, making them a good choice for rehabilitation. In addition, they are cost-effective, making them affordable for many users.

The IMU-based Mocap system also has disadvantages [8]: (1) IMU sensors suffer from drifts, which causes the sensing results to change over time. (2) The wearing method is correlated with the slight change in relative position when moving the skin or loosening the fixed device. (3) Magnetometers can be influenced by external magnetic field. These drawbacks will mainly affect the accuracy of the result. To address these problems, studies have proposed several solutions, such as applying an algorithm to revise the data, using auto-calibration for the drift, and fusing with other systems for comprehensive measuring.

1.2. The necessity of this review

Given the multiple benefits of the IMU-based Mocap technology in rehabilitation and the aforementioned rapid development, we strongly believe that it is essential to summarize its applications in rehabilitation and how to perform them. In this review, we will provide an overall insight into the aforementioned applications in the field of rehabilitation from 2013 to 2022 and discuss the methods for performing.

In recent years, there has been an increasing number of literature reviews on Mocap in the field of rehabilitation. We consider the current reviews from two perspectives: technology-based and application-based. Technology-based reviews focus on the design and development of Mocap systems. For example, Yahya et al. [5] discussed upper-limb sensing technology, whereas Walmsley et al. [9] focused on upper-limb RoM measurement. Díaz et al. [10] proposed the development of wearable sensors for rehabilitation assessment. All of these studies highlight the principles and advancements of the Mocap technology. Application-based reviews, on the other hand, demonstrate the use of the Mocap technology in specific applications. Alarcón-Aldana et al. [11] described the use of Mocap in the field of rehabilitation combination with videogames, whereas Figueiredo et al. [12] studied the assessment of lower limb orthosis-based interventions after strok. Furthermore, Knippenberg et al. [13] focused on training with a markerless Mocap system. These studies demonstrate the benefits of Mocap in different applications, but they are relatively independent and only focus on the specific applications.

We assumed a scenario in which researchers who have developed state-of-the-art IMU-based Mocap systems wish to apply them in the field of rehabilitation. Some studies, such as those by Wang et al. [14] and Porciuncula et al. [15], analyzed the development of the technology and its potential applications in clinical settings, but either summarized upper-body rehabilitation or focused only on wearable sensors, not Mocap systems. Therefore, we conducted this review, which aimed to describe the overall system design of IMU-based Mocap and provide clear instructions on specific rehabilitation applications that can be implemented using assessment, training, and clinical processes in rehabilitation.

Table 1
Search strategy.

Databases	Searching keywords
Scopus IEEE Xplore PubMed Web of Science	("Motion Captur*" OR "Mocap") AND ("IMU" OR "inertia* sensor" OR "Accelerometer" OR "wearable sensor" OR "Inertial measurement unit") AND ("rehabilitation" OR "Postoperative treatment" OR "human body analysis")

1.3. Contributions of this review

Briefly claim the contribution of this review:

(1) To give an overview of the current IMU-based Mocap system design used in the field of rehabilitation.

(2) To discuss in what specific application IMU-based Mocap systems can be used and their detailed implementation.

(3) To summarize and preview the future development both in the system design and the implementation method considering the current limitation.

2. Materials and methods

2.1. Data source and search strategy

This review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines [16]. The literature search was conducted using Scopus, IEEE Xplore, PubMed, and Web of Science. The time range was set to the last 10 years, from January 2013 to August 2022 (see Fig. 1).

The screening process for this research involved dividing the focus into three categories: motion capture technology, specific IMU sensors, and applications in the field of rehabilitation. The specific search strategy is presented in Table 1. It is worth noting that IMUs are also referred to as wearable sensors in some papers. To broaden the scope of rehabilitation, we also included synonymous terms, such as postoperative treatment.

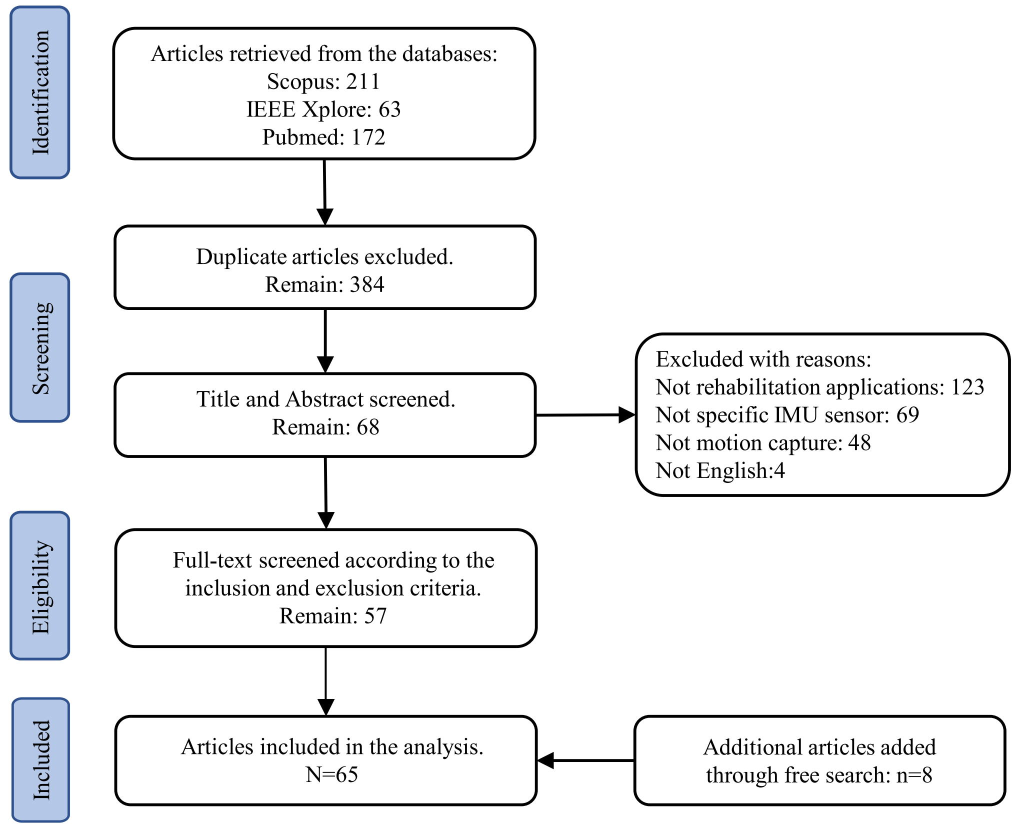

Fig. 1. Flowchart of searching result.

2.2. Inclusion criteria

To ensure the relevance and reliability of the selected literature, strict inclusion criteria were applied during the selection and screening processes. Specifically, only literature written in English and published between 2013 and August 2022 were included in this review. Furthermore, we considered only journal articles or conference papers that focused on IMU-based motion capture system (not OMC or virtual IMU). We also included research that fused IMU with other sensors. Also, the research must have contained a specific method for applying the system in the context of rehabilitation, either designed a system for a specific disease (e.g., stroke and cerebral palsy) or focused on general rehabilitation (e.g., gait analysis and monitoring). In addition, the research must have contained specific data that was quantified to argue the performance of the system and must have been method-oriented with a clear application direction.

2.3. Exclusion criteria

Articles focusing only on the design of a high-performance IMU-based Mocap system and lacking specific information on how the system is applied in a particular field have been excluded from this review. For example, Slade et al. [17] developed an open-source real-time IMU-based Mocap system for general purpose but did not provide details in rehabilitation; thus, it was excluded from this review. Therefore, the implementation in rehabilitation is essential. In addition to the aforementioned criteria, the research must focus on capturing human motion, either full body or segment motion. Studies on animals and objects were excluded from the review.

Table 2 is organized by the date the study was published. This allows a clear identification of the trend of the studies.

3. Results

After the exclusion and literature screening, a total of 384 articles were searched, and 65 papers were selected for analysis. The overall features are presented in Table 2.

The selected articles may be divided into rehabilitation applications, target population, and system measurement. This classification system helps distinguish the implementation, functionality, and effects of the different IMU-based Mocap systems in the field of rehabilitation. The first dimension is the rehabilitation application, which lists all the application scopes. It may be classified into rehabilitation assessment and rehabilitation training according to the functional purpose of the application. The second dimension is target population, which indicates the target population will be focused on in the different applications. The third dimension is system deployment and measurement, which classifies the reviewed articles according to the measured or analyzed parameters of the IMU-based Mocap system. More details are discussed in the following sections.

3.1. Rehabilitation application

We divided the rehabilitation applications of the IMU-based Mocap system into two categories: assessment and training. Assessment is crucial in rehabilitation as it helps determine the severity of a patient's condition and the effectiveness of the rehabilitation plan. Furthermore, it involves evaluation of a patient's current circumstances, rehabilitation goals, and performance, as well as monitoring of their motion and analysis of relevant parameters. Rehabilitation training involves performing specific tasks or programs to help patients improve their performance, typically following an assessment. The training system has to provide interventions or feedbacks in real time to

Table 2
Summary of the included studies.

References	IMU system		Target population	Rehabilitation application	
	Number	Measurement			
Zhang et al. [18]	Full body (n = 17)	CoM, SA, GMM	Sports injured athletes	Assessment	Use IMU to aid in the assessment of sporting injuries and to monitor the progress
Zecca et al. [19]	Lower limbs (n = 7)	JA	Gait impairment	Assessment	Walking assessment
Yurtman and Barshan [20]	Lower limbs (n = 5)	Body motion	Not specified	Assessment	Classification and evaluation of therapy exercises using the MTMM-DTW algorithm
Lee et al. [21]	Upper arm (n = 7)	RoM	Stroke	Assessment	Smartphone-centric system for the range-of-motion assessment
Moreira et al. [22]	Hand (n = 11)	Finger flexion	Not specified	Assessment	Design and evaluation of a low-cost motion-capture glove for hand function assessment
Carpinella et al. [23]	Wrist (n = 1)	Accelerometer and gyroscope signals	Multiple sclerosis	Assessment	Quantitative assessment of upper-limb motor function
Papi et al. [24]	Lower limbs (n = 2)	Kinematics	Osteoarthritis patients	Assessment	Provision of objective measures of performance
van Meulen et al. [25]	Full body (n = 17)	Arm movement	Stroke	Assessment	Provision of patient-specific performance assessment for stroke patients in in-home setting
Tedesco et al. [26]	Lower limbs (n = 4)	JA, STP	Sports injured athletes	Assessment	Provision of a biomechanics assessment
Li et al. [27]	Upper arm (n = 4)	Kinematics	Stroke	Assessment	Quantitative assessment of the performance of the single-task upper-limb movements
Ayachi et al. [28]	Full body (n = 17)	Body segment posture	Older adult	Assessment	Auto-detection of daily living activities
Zhao et al. [29]	Foot-mounted (n = 2)	STPs	Cerebral thrombosis patients	Assessment	An INS system for assessing gait performance
Zhang et al. [30]	Full body (n = 11)	Joints orientation	Not specified	Assessment and Training	An evaluation system for assessing and comparing with experts to perform evaluation and display
Xu et al. [31]	Lower limbs (n = 8)	FPA	Gait impairment	Training	Use of haptic IMU to train FPA
Woodward et al. [32]	Lower limbs (n = 1)	Movement and muscle activity	Cerebral palsy	Assessment	Fusion of IMU and MMG to measure motion and muscle and classify
Visi et al. [33]	Lower limbs, shanks (n = 2)	STPs	Stroke	Assessment	Measurement of trends in comparative left vs right mean stride lengths
Villeneuve et al. [34]	Upper arm, wrist (n = 2)	Body motion	Not specified	Assessment	IMU for smart home health care, monitoring, and assessment
Valtin et al. [35]	Hand (n = 15)	JA	Stroke	Assessment	Assessment of hand function and feedback applications
Ranganathan et al. [36]	Trunk, upper arm, forearm segment (n = 3)	Body motion	Stroke	Assessment	Mocap used for assessing and monitoring compensatory movements
Delrobaei et al. [37]	Full body (n = 17)	Kinematics	Dyskinesia, PD	Assessment	Generation of objective scores for assessment
Yi et al. [38]	Lower limbs (n = 2)	JA	Duchenne muscular dystrophy in children	Assessment	Fusion of IMU and EMG to diagnose and evaluate therapy and to assist exoskeleton control
Wang et al. [39]	Lower limbs (n = 4)	STPs	Gait impairment	Assessment	Estimation of individual step length and spatial asymmetry of gait
Kutilek et al. [40]	Upper arm (n = 4)	Kinematics	Not specified	Assessment	Quantitative evaluation of the movement activity of the upper limbs during rehabilitation
Karatsidis et al. [41]	Lower limbs (n = 7)	FPA	Gait impairment	Training	AR feedback wearable Mocap system for gait retraining
Held et al. [42]	Full body (n = 14)	Body segment posture	Stroke	Assessment	Evaluation of the rehabilitation progress in a clinical and home environment
England et al. [43]	Lower limbs (n = 4)	Kinematics	Post-operative ACL patients	Training	Measurement of kinematics and incorporation of the expertise into feedback for the wearer
Sharif Bidabadi et al. [44]	Lower limbs (n = 1)	Foot pitch angle	Gait impairment	Assessment	Validation of the foot pitch angle measurement in gait analysis

(*continued on next page*)

Table 2 (*continued*).

References	IMU system		Target population	Rehabilitation application	
	Number	Measurement			
Teufl et al. [45]	Lower limbs (n = 7)	JA, STPs, kinematics	THA	Training	Application of SVM for classification for incorporation in a mobile gait-feedback system
Marín et al. [46]	Full body (n = 12)	Body motion	Spasticity patient	Assessment and training	Guidelines for the integration of Mocap gait analysis in hospital rehabilitation
Liu et al. [47]	Finger, wrist (n = 2)	Kinematics	Stroke	Assessment	Application of machine learning to monitoring hand use
Lin et al. [48]	Hand (n = 16)	Kinematics	Stroke	Assessment	Provision of hand motion to physicians for adjusting rehabilitation treatments
Lefeber et al. [49]	Lower limbs (n = 2)	STPs	Stroke	Assessment	Validation of the availability of inertial physilog sensors in gait analysis
Konrath et al. [50]	Full body (n = 17)	Body motion	Osteoarthritis patients	Assessment	Estimation of the knee adduction moment and tibiofemoral joint contact force
Kayaalp et al. [51]	Lower limbs (n = 2)	RoM	Orthopedic patients	Assessment	Validation of the availability of IMU in monitoring postoperative rehabilitation
Beange et al. [52]	Lumbar (n = 2)	Spine flexion–extension	Low back pain	Assessment	Assessment of functional movement quality and control of the lumbar spine
Weygers et al. [53]	Lower limbs (n = 2)	JA	Gait impairment	Assessment	Validation of the availability of IMU in gait analysis
Warmerdam et al. [54]	Upper arm, wrist (n = 1)	Arm swing parameters	PD patients	Assessment	Evaluation and quantification of arm swing using IMU and sensor-based algorithm
Tsakanikas et al. [55]	Head and wrist (n = 2)	Body motion	Not specified	Assessment and Training	Embed IMU, pressure insoles, and RGB camera to develop a virtual coaching ecosystem
Shin et al. [56]	Lower limbs (n = 7)	Kinematics	Stroke	Assessment	Quantifying dosage of physical therapy
RajKumar et al. [57]	Upper arm (n = 5)	RoM	Not specified	Assessment	RoM assessment
Qiu et al. [58]	Lower limbs (n = 7)	STPs	Stroke	Assessment	Gait posture evaluation for subjects with unbalanced gaits
Marin et al. [59]	Lower limbs (n = 8)	Kinematics	Spasticity patient	Assessment	Assessment of improvements in patients following interventions
Hutabarat et al. [60]	Lower limbs, shoes (n = 2)	STPs	Gait impairment	Assessment	Quantitative gait assessment using only two IMU sensors
De Baets et al. [61]	Full body (n = 9)	RoM	Adhesive capsulitis	Assessment	Evaluation of disease progression in clinical settings
Aranda-Valera et al. [62]	Lumbar (n = 2)	Kinematics	Axial spondyloarthritis patient	Assessment	Evaluation of spinal mobility in individuals
Werner et al. [63]	Lower limbs (n = 2)	STPs	SCI patients	Assessment	Gait assessments using IMU
Wang et al. [64]	Lower limbs (n = 2)	STPs and kinematic parameters	Gait impairment	Assessment	Proposal of a new gait variable to derive an IMU-based gait normalcy index for evaluation
Vargas-Valencia et al. [65]	Lower limbs, shank, and thigh (n = 2)	JA	Knee injury	Assessment	Fusion of IMU and POF to detect knee angle for assessment
Tsilomitrou et al. [66]	Upper arm (n = 2)	Body motion	Not specified	Training	System for a patient's progress supervision during rehabilitation exercises
Schlage et al. [67]	Lower limbs (n = 5)	JA	Knee-injured patients	Assessment	Mocap used as an alternative long-term measurement method
Parker et al. [68]	Lower limbs (n = 7)	Kinematics	Older adult	Assessment	IMU Mocap used to compare the different walking conditions
Monoli et al. [69]	Lower limbs (n = 2)	JA	Gait impairment	Assessment	Execution of underwater gait assessment
Hwang and Effenberg [70]	Full body (n = 16)	Head trajectories	Gait impairment	Assessment	Gait symmetry analysis
Hou et al. [71]	Full body (n = 6)	STPs	Gait impairment of healthy young adults	Assessment	Gait assessment in healthy young adults
Fan et al. [72]	Lower limbs (n = 4)	Knee flexion, abduction, and internal rotation	ACL injury patient	Assessment	Knee flexion, abduction, and internal rotation estimation during ACL injury risk assessment tests
Di Paolo et al. [73]	Full body (n = 15)	Kinematics	ACL injury patient	Assessment	Quantification of joint kinematics for return-to-sport assessment
Arens et al. [74]	Lower limbs, shoes (n = 2)	STPs	Stroke	Training	Real-time gait metric estimation, exo-suit-assisted gait training
Patel et al. [75]	Lower limbs (n = 2)	STPs	Gait impairment	Assessment	Validation of the availability of IMU in gait analysis

(*continued on next page*)

Table 2 (*continued*).

References	IMU system		Target population	Rehabilitation application	
	Number	Measurement			
Mittag et al. [76]	Wrist (n = 1)	Inclination	Children with cerebral palsy	Training	Designing of a method for real-time control of exergames of cerebral palsy children
Mallat et al. [77]	Upper arm, hand (n = 3)	JA	Poststroke patients	Assessment	Proposal of an affordable Mocap fusing IMU with AR validated with six rehabilitation tasks
Li et al. [78]	Lower limbs (n = 7)	Kinematics	Gait impairment	Assessment	Development of a body sensor network for reconstruction movement and a neural network for classifying gait phase
Sung et al. [79]	Lower limbs (n = 1)	JA	Gait impairment	Assessment	Proposal of a method fusing IMU and RNN for measuring multi-joint angle
Camargo et al. [80]	Lower limbs (n = 4)	Kinematics	Not specified	Training	Fusion of IMU, EMG, and goniometers to anticipate joint moment
Gu et al. [81]	Lower limbs (n = 2)	Kinematics	Not specified	Assessment	Use of 2 IMU sensors to estimate muscle activity during walking
Tedesco et al. [82]	Lower limbs (n = 2)	RoM	Knee-injured patients	Assessment and training	Designing of a multi-sensor (EMG, IMU) wearable system for knee rehabilitation

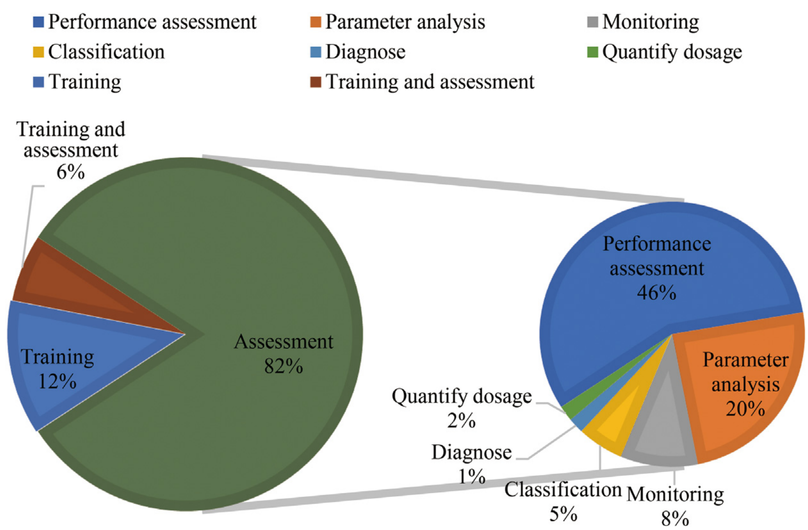

Fig. 2. The proportion of each classification.

help patients achieve better outcomes. Fig. 2 summarizes the ratio of rehabilitation assessment and training and the specific application they are used for.

3.1.1. Rehabilitation assessment

Among all the rehabilitation applications, assessment accounts for the most proportion, which includes performance evaluation, parameter analysis, motion classification, activity monitoring, quantified dosage, and diagnosis.

A total of 30 studies [19,22–27,29,35,37,40,42,48,49,52–54,58–61,63,64,67–71,75] suggested that the IMU-based Mocap system can be used to conduct performance evaluation.

Among these performance evaluations, 12 articles [19,29,49,53,58–60,62–64,69,71,75] focused on gait performance assessment. Marin et al. [59] proposed a magnitude-based decision statistical method for analyzing gait in order by comparing two different sessions from single patients. Some studies [49,53,75] validated the availability of IMU-based Mocap system used in gait analysis and further Zhao et al. [29] designed a system with a zero velocity update (ZUPT) assist inertial navigation system (INS) algorithm to achieve more accurate quantified gait parameters. Hutabarat et al. [60] used 2 IMUs to extract 17 gait features to quantify gait analysis. Aside from the general gait assessment, Monoli et al. [69] conducted underwater gait assessment due to the robustness of the IMU-based Mocap system. Furthermore, Wang et al. [64] proposed a new gait variable to derive an IMU-based gait normalcy index for evaluation. Except for the gait performance, other performance evaluation studies focused on the upper-limb performance evaluation, mostly as [25]. Some studies, such as Li et al. [27] and Kutilek et al. [40], also quantified the upper-limb performance via kinematics analysis, and [54] achieved such quantification using arm swing parameters. Furthermore, for the compactness of MEMS IMUs, they can be set on fingers for assessing the hand function by executing different hand motions [35] [48]. Although most of these studies were set in laboratory environment, De Baets et al. [61] and Held et al. [42] conducted upper-limb evaluation in the clinical environment. Meanwhile, Schlage et al. [67] used IMU-based Mocap as a long-term assessment method to generate adequate data for guiding flexible therapy. Aside from the lower- and upper-limb assessment, Beange et al. [52] used the IMUs to assess lumbar spine control and functional movement.

As for the monitoring purpose, Kayaalp et al. [51] validated the availability of IMU in the monitoring of postoperative rehabilitation. Zhang et al. [18], Villeneuve et al. [34] and Ranganathan et al. [36] aid assessment with monitoring. Liu et al. [47] develop a new pipeline using machine learning for minitoring.

Table 3
Target population.

Target population		Reference
Neurological Rehabilitation	Stroke	[21,25,27,33,35,36,42,47–49,56,58,74,77]
	Spasticity	[46,59]
	Cerebral palsy	[32,76]
	Parkinson's disease	[37,54]
	Spinal cord injury	[63]
	Other neurological diseases	[23,29,64]
Musculoskeletal Impairment	Osteoarthritis	[24,50,51,62]
	Anterior cruciate ligament (ACL) injury	[43,72,73]
	Other musculoskeletal impairment	[18,26,38,45,52,61,65,67,82]
General Rehabilitation	Gait impairment with no specified disease	[19,31,39,41,44,53,60,69–71,75,78,79]
	The elder	[28,68]
	Not specified	[20,22,30,34,40,55,57,66,80,81]

Another important aspect of assessment involves the use of IMU-based Mocap to analyze various parameters. These parameters can be derived from general movements or raw sensor data and act as indicators for assessment. For example, the RoM is often analyzed, as observed in the studies by RajKumar et al. [57], whereas Lee et al. [21] used a smartphone-centric system for RoM assessment. Joint rotation is also commonly measured, as demonstrated by Fan et al. [72] in their research on the use of rotation as a measure for injury and disease rehabilitation.

Other assessment applications, such as classification, diagnosis, and dosage quantification, are also applications of the IMU-based Mocap system for rehabilitation assessment. Furthermore, some fusions are applied to achieve multi-model assessment. These fusion technologies provide supplementary information such as muscle activities with the introduction of other sensors. Woodward et al. [32] fused the IMU with mechanomyography (MMG) to measure the motion and the muscle activity to perform classification. Yi et al. [38] fused IMU with electromyography (EMG) to diagnose and evaluate therapy, which can also cooperate with the exoskeleton for assistance control. Vargas-Valencia et al. [65] fused polymer optical fiber (POF) to detect joint angles to conduct an assessment. Mallat et al. [77] proposed an affordable motion capture system that combines IMUs with augmented reality markers tracked with an affordable RGB camera and validated it with six rehabilitation tasks. These multi-model assessments provide additional information, such as muscle data, which cannot be obtained using IMU alone; they also play an important role in dynamic assessment. In addition, multi-model systems show potentials for assisting other devices in performing rehabilitation therapies.

3.1.2. Rehabilitation training

Unlike rehabilitation evaluation with miscellaneous parameters, rehabilitation training has some fixed characteristics, namely, training content and intervention or feedback.

At present, there are relatively few articles that have used IMU to evaluate training programs. Feedback is a crucial aspect of training applications. It can remind the user or assistive device to adjust the training content or guide a change of posture. Real-time motion recovery systems, such as those proposed by Tsilomitrou et al. [66] and England et al. [43], provide users with information on their current motion and can be used for monitoring training progress and providing customized training plans to experts. Timmermans et al. [7] designed a technology-supported task-oriented arm training regime (T-TOAT) using tracking sensors, an exercise board, and a software-based toolkit to improve the arm performance of stroke patients. T-TOAT was found to significantly improve patients' health-related quality of life, both physically and mentally. Virtual reality (VR) can also be used as a feedback device to provide a more immersive environment for the user, as shown by Karatsidis et al. [41]. In addition to visual feedback, IMU can provide systematic feedback to facilitate the control of external devices during training. For example, Teufl et al. [45] used support vector machine (SVM) classification with IMU to create a mobile gait-feedback system, whereas Mittag et al. [76] used IMU to perform real-time control of exergames for children with cerebral palsy. Arens et al. [74] used IMU to measure real-time gait metric estimation, which was used to assist in exo-suit gait training, and Camargo et al. [80] adopted the fusion of IMU, EMG, and goniometers to anticipate joint movement during ambulation tasks.

Other studies that include both assessment and training, such as [30,46,55], are presented below. They all used visual feedback to give the users an intuitive obverse of their real-time training. Zhang et al. [30] and Tsakanikas et al. [55] developed virtual coaching ecosystems containing the expert guide, visual feedback, and systematic analysis. Marín et al. [46] provided some guidelines to integrate Mocap in hospital rehabilitation, which contained both assessment and training for gait analysis. Tedesco et al. [82] designed a multi-sensor including EMG and IMU wearable system for knee rehabilitation.

3.2. Target population

In this part of the review, we inventoried the target population for the application of the IMU-based Mocap system in rehabilitation. To better understand the trend of the use of the IMU-based Mocap system and determine which target population it is most effective for, we divided the target population into three categories based on previous research [14]: neurological rehabilitation (including stroke, spasticity, cerebral palsy, and Parkinson's disease), musculoskeletal impairment (including osteoarthritis and other orthopedic diseases), and general rehabilitation (with not specific pathology).

The different target populations are listed in Table 3. However, most studies focused on general rehabilitation ($n = 25$), in which healthy people were recruited in the experiment design and the researches did not focus on specific pathology. Among these, gait is mostly investigated with 13 studies included. Parker et al. [68] and Ayachi et al. [28] focused on the elder as the target population. Among neurological problems ($n = 24$), stroke appears to be the most worrisome, with 14 studies [21,25,27,33,35,36,42,47–49,56,58,74,77] designing the IMU-based Mocap system for stroke patients. Neurological diseases include spasticity [46,59], cerebral palsy [32,76], Parkinson's disease [37,54], spinal cord injury [63], and other diseases [23,29,64].

As for the musculoskeletal impairment ($n = 16$), four studies [24,50,51,62] focused on osteoarthritis. Musculoskeletal diseases include anterior cruciate ligament (ACL) injury [43,72,73], and other musculoskeletal diseases [18,26,38,45,52,61,65,67,82].

Besides, a relative large porpotion of studies did not specified any target population and provided general used systems, for

Table 4
Classification based on system deployment.

IMU placement		Reference
Upper limbs	n = 1	[23,54,76]
	n = 2	[34,47,52,55,66]
	n = 3	[36,77]
	n = 4	[27,40]
	n = 5	[57]
	n = 7	[21]
	n = 11	[22]
	n = 15	[35]
	n = 16	[48]
Lower limbs	n = 1	[32,44,79]
	n = 2	[24,29,33,38,49,51,53,60,62–65,69,74,75,81,82]
	n = 4	[26,39,43,72,80]
	n = 5	[20,67]
	n = 6	[71]
	n = 7	[19,41,45,56,58,68,78]
	n = 8	[31,59]
	n = 9	[61]
Full body	n = 11	[30]
	n = 12	[46]
	n = 14	[42]
	n = 15	[73]
	n = 16	[70]
	n = 17	[18,25,28,37,50]

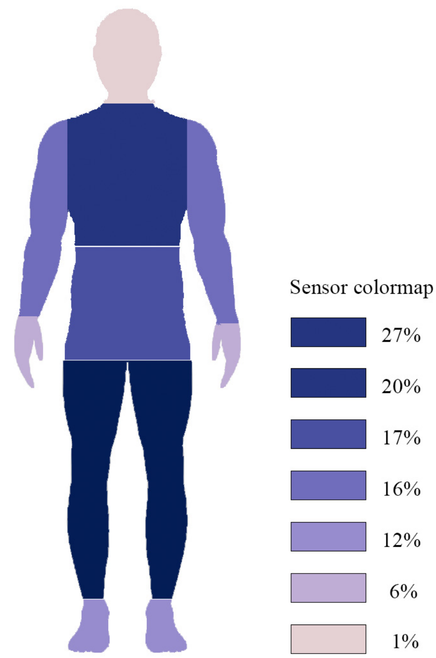

Fig. 3. IMU sensor colormap of different segments (research frequency for different segments).

example Yurtman and Barshan [20] derived a novel algorithm to detect and evaluate therapy exercises and some of them designed a monitoring system as [34,55,66].

3.3. System deployment and measurement

As for the different rehabilitation applications, system deployment and measurement parameters are important for particular rehabilitation usage. System deployment calculates the number of IMUs used and their placement. Measurement parameters can be classified into several dimensions: human kinematics focuses on any inclusive joints; gait parameters focus exclusively on the lower limbs; and body motion focuses on whole-body movement.

3.3.1. System deployment

Table 4 presents the sensor placement for all the studies included, and Fig. 3 shows the colormap of research hotspots, highlighting the distribution of areas with the most sensor placement. Accordingly, for the upper-body analysis, two IMU sensors are usually selected and placed on the upper arm and forearm. For the lower-limb analysis, two IMU sensors are selected and placed on each of the legs for gait analysis and the thigh and shank for knee joint analysis. As for the full-body analysis, 17 IMUs are usually selected and placed symmetrically on both sides, including at the feet, lower legs, upper legs, hands, lower arms, upper arms, shoulders, pelvis, back, and head. Hutabarat et al. [60] and Arens et al. [74] designed an in-shoe Mocap system, and each IMU was placed on one side of the shoes. Tsakanikas et al. [55] and Hwang and Effenberg [70] tracked head motion with one IMU sensor mounted on the head. Some studies focused on hand function, and their IMU setups significantly varied. Liu et al. [47] analyzed hand function using 2 IMUs mounted on the hand or the finger, whereas Lin et al. [48] placed 16 IMUs on the hand for their customized hand-tracking glove, which could perform sophisticated motion tracking into finger-level precision.

3.3.2. Measurement

Table 5 presents the system measurements of all the selected studies in three categories: human kinematics, gait parameters, and body motion.

When measuring human kinematics, most of them are evaluated through the measurement of joint orientation or direct use of kinematics data for analysis. Generally, joint orientation is used in performance evaluation in lower-limb gait analysis. Tedesco et al. [26], Schlage et al. [67], Monoli et al. [69], Zecca et al. [19], and Weygers et al. [53] measured the joint angles of the lower limbs which provides an available method for gait assessment. Kinematic data were used to generate objective evaluation scores to assess the performance, such as [37]. In the gait analysis, the spatio-temporal parameters are considered standard parameters, which are the most measured in the studies by [29,33,39,49,58,60,63,64,71,74,75]. Furthermore, foot progression angle (FPA) is always used in the training process of rehabilitation, as studies by Xu et al. [31],Karatsidis et al. [41] used haptic and AR to perform rehabilitation training.

In the measurement of human body motion, body segment motion is usually measured to conduct both assessment and training. In [83], this parameter was used to recover human motion. In [55], IMU, pressure insoles, and RGB cameras were used to recover body motion. Visualization was easy to perform using this developed virtual coaching ecosystem. In [70], head trajectories were measured to analyze gait symmetry. In the study by [32], movement and muscle activity were measured by the fusion of IMU and MMG for motion classification. Furthermore, the arm swing parameters were measured in [54] to evaluate and quantify arm swing using IMU and a sensor-based algorithm.

4. Discussion

This article reviews the rehabilitation application of the IMU-based Mocap system over the last 10 years. All the articles included here were reviewed from three perspectives: rehabilitation application, target population, and system deployment and measurement. From these three perspectives, we expect to provide an overall demonstration of the IMU-based Mocap application in rehabilitation and introduce a general deployment method. In this part, we will discuss each of the separate dimensions and analyze the result and the possible reasons. Then,

Table 5
Classification based on measurement parameters.

Measurement parameters		Reference
Human kinematics	Range of motion	[21,51,57,61,82]
	Joint orientation	[19,22,26,30,35,38,45,52,53,65,67,69,72,77,79]
	Kinematics	[23,24,27,37,40,43,45,47,48,56,59,62,64,68,73,76,78,80,81]
Gait parameters	Spatio-temporal parameters	[29,33,39,45,49,58,60,63,64,71,74,75]
	Foot progression angle	[31,41]
	Centre of mass	[18]
	Foot pitch angle	[44]
Body motion	Body segment motion	[20,28,34,36,42,46,50,55,66]
	Head trajectories	[70]
	Arm swing parameters	[25,54]
	Movement and muscle activity	[32]

based on the literature reviewed, we would like to provide some objective opinions on future system development and provide a preview of application trends.

4.1. Rehabilitation application

Various applications have been applied among the selected articles, including performance assessment, parameter analysis, monitoring, classification, diagnosis, dosage quantification, and training.

The results indicated that the use of IMU-based Mocap in rehabilitation assessment is quite mature. Many articles [49,53,75] validated the acceptable accuracy of the IMU sensor compared with the gold standard optical Mocap.

Among the 80% of the assessment, 46% is about performance assessment, as it is the major application in the assessment. For most of the performance assessments, they have a pre-existing metric as a reference, for example, van Meulen et al. [25] provided the Fugl-Meyer Assessment scale (uFMA) metric for arm movement evaluation, and Delrobaei et al. [37] performed Unified Dyskinesia Rating Scale (UDysRS) for Parkinson Rating.

These metrics have been considered a gold standard in clinical medicine, and the IMU-based Mocap system has the ability to quantify the results and better fit the metric.

Considering that in the current rehabilitation medical field, doctors usually assess the patient's performance based on several fundamental features, such as joint angles and RoM, which are always intuitive and mostly rely on experience. Delrobaei et al. [37] proposed the use of wearable technology to generate severity scores. Researchers may use IMU to generate credible metrics concurrent with existing metrics to perform a better-quantified assessment.

Besides, the convenience of deployment and compactness of the sensor size also provide a possible chance for rehabilitation assessment. Article Zecca et al. [19] proposed the use of ultra-miniaturized, portable IMU for long-term assessment with better wearing experience. The exclusive property of IMU, which is being free from occlusion and illumination, enables it to perform remote and extreme measurements. For example, Monoli et al. [69] has applied IMU for underwater gait analysis, whereas Lin et al. [48] proposed a modular data glove with 16 IMUs to measure the wearer's finger RoM, with the lowest accuracy being 2%.

Compared with articles on assessment, with a proportion of 85%, the articles focusing on training alone are relatively few, with a proportion of only 10%. Although training is still an important part in the rehabilitation therapy process for studies, as shown by Spooren et al. [84], the knowledge and evidence of Mocap use for training are scarce. Here, we proposed some possible reasons for the unbalanced ratio of rehabilitation assessment and training.

Rehabilitation training is time-consuming and costly in clinical practice, which means they always need to have a long-term training process to meet a certain treatment circle. Timmermans et al. [7] designed a training protocol lasting for 8 weeks. Measurements were performed not only after 4 and 8 weeks of training but also 6 months post-training. This validation period of the rehabilitation training is quite long. Unless the purpose of such studies is to confirm the curative effect of a newly proposed training method, few participants would be willing to participate. Furthermore, during the training program, therapists also need to be involved in assisting and providing instructions. For researchers, it definitely increases the difficulty of performing the experiment.

The accuracy of Mocap technology is highly related to its price, and for long-term training, the sensor has to be equipped with sufficient battery to ensure battery life. As mentioned by Xu et al. [31], their sensor has roughly 1.5 h of battery life, which is enough to meet most rehabilitation demands but could be insufficient for longer training or monitoring. We investigated the systems in the studies included and found that the main reason for the problem of low battery life is the high power consumption of the signal transimission module. The majority of signal transmission pathways in these systems are WIFI, leading to a high power consumption, whereas a relatively low proportion make the use of Bluetooth. We proposed the development of a more efficient chip or the use of a power-saving transmission method, which would make the system more competent for long-term application.

Despite the relatively low cost of IMU sensors, it is still unaffordable for general patients to perform home-based training. According to Knippenberg et al. [13], markerless Mocaps (e.g., Kinect) are frequently used owing to their ease of deployment and lower price.

Furthermore, Timmermans et al. [7] and Knippenberg et al. [13] stated that current studies for rehabilitation training lack novel task-oriented training. Thus, we proposed that future technology developments should take up the challenge to combine IMU with a task-oriented approach.

Thus, we believe that combining VR or AR with another novel task-oriented training content is also a promising trend in rehabilitation training. Karatsidis et al. [41] combined an IMU Mocap system and AR to perform gait retraining to alter the FPA.

The integration of Mocap and AI has the potential to significantly improve the efficiency of Mocap systems. For example, according to Sung et al. [79], the use of AI can allow Mocap systems to use fewer sensors while still accurately measuring multi-joint angles using recurrent neural networks. In addition, Li et al. [78] demonstrated the use of neural networks to classify gait phases in Mocap systems. Overall, the incorporation of AI into Mocap technology shows great promise for improving accuracy and efficiency.

Based on the rehabilitation applications, we can summarize that the applications of IMU-based Mocap systems mainly focus on the repair of human motion function owning to the motion information retrieved from the system. However, performing rehabilitation only based on kinematics is insufficient; research shows that muscle activity also plays an important role in rehabilitation [85].

In recent years, there has been an increasing focus on the fusion of different sensors to create multi-modal systems for rehabilitation. These systems provide multiple perspectives for analysis and can help reduce errors caused by IMU sensors. For example, Vargas-Valencia et al. [65] used IMU sensors in combination with POF to measure knee angle and found that the fusion of these two sensors led to more accurate results and was not influenced by magnetic fields.

Multi-modal systems are often necessary due to the limited measurement dimensions of IMU sensors, which may not provide all the necessary data on their own. To add information, other types of sensors are often introduced. For example, Yi et al. [38] combined IMU sensors with EMG signals to automatically diagnose the progress of Duchenne muscular dystrophy, whereas Woodward et al. [32] used the fusion of IMU and MMG sensors to measure motion and muscle activity to classify human activities. Tedesco et al. [82] used EMG and IMU sensors to create a multi-sensor knee rehabilitation system, in which the data measured by the EMG sensors could help improve evaluation efficiency and accuracy.

In addition to providing additional data, the use of multiple sensors can also help overcome the limitations of IMU sensors, such as limited battery life and accuracy. For example, Tsakanikas et al. [55] used IMU sensors in combination with pressure insoles and an RGB camera to develop a virtual coaching ecosystem. Similarly, Mallat et al. [77] proposed the use of IMU sensors in combination with AR for an affordable Mocap system for rehabilitation tasks.

Overall, the potential of multi-modal systems is clear, and we believe that the fusion of other sensors will be important for comprehensive rehabilitation applications in the future.

4.2. Target population

The target population is generally classified into three dimensions: neurological rehabilitation, musculoskeletal impairment, and general rehabilitation. For neuro-rehabilitation, stroke patients are the most studied group. Stroke affects the patient's motion ability and causes disability or limitation in joint orientation. About 14 articles focused on stroke rehabilitation, whereas other neurological diseases shared a relatively low ratio.

A total of 16 articles were included in the analysis of musculoskeletal impairments, with the majority of studies focusing on osteoarthritis ($n = 4$). Additionally, there were 25 studies that examined general rehabilitation using IMU-based motion capture technology. These findings demonstrate the versatility of this technology, which can be used not only for specific diseases but also for broader applications such as diagnosis, disease prevention, and daily monitoring. As a result, it has the potential to be widely accessible to the general public.

Many researches focused on the target population of a specific disease, however, typically in their experimental design section, they still chose healthy people as experiment subjects. This is partly because of the difficulty in performing clinical experiments and the patient's willingness to participate.

4.3. System deployment and measurement

Our review also indicated that knowing the detailed system deployment and the parameter measured by the system is beneficial for the implementation of similar applications and provides a guideline for further research.

Regarding the physical property of IMU sensors, they are usually mounted on the target body segment to measure the kinematics of the body part. Thus, the IMU placement is divided according to the distribution of sensors. Among them, the lower limbs are more usually studied, and in most cases, two IMUs are placed on the foot. This may be because gait analysis of the lower limbs has standardized research paradigms that are repeatable and easier to execute. Furthermore, the wearing complexity and battery life may also be the confining conditions to limit full body or long-term analysis.

To address the difficulty of wearing, some studies have designed integrated systems to locate the fixed IMUs into clothes, providing easy-to-wear properties and decreasing the impact of soft tissue artifacts. Hutabarat et al. [60] and Arens et al. [74] designed to put the IMU sensors into shoes to develop an in-shoe system, and Lin et al. [48] modulated a data glove containing 16 IMUs.

For the system measurement, we divided it from fundamental kinematic to complicated body motions. For human kinematics, joint orientation is mostly measured for convenience and obviousness, followed by specific gait parameters, such as spatio-temporal parameters. This parameter is the most commonly used in gait analysis, with 12 studies included. Furthermore, the trend of measuring human body motion, especially specific motion, is increasing. With these measured motions, classification can be easily performed; they can also provide direct visual feedback to the user that is essential for rehabilitation training.

4.4. Inspiration for development tendency

The development of IMU-based Mocap system is still in its infancy, and many applications can be developed. A summarized probable trend of the application of IMU-based Mocap system in the field of rehabilitation is presented below:

(1) Multiple sensor fusion with IMU can lead to a multi-modal system to provide a comprehensive rehabilitation assessment.

(2) In-home rehabilitation training systems, coupled with long-term monitoring and assistance from other complementary equipments, can provide quasi-clinical rehabilitation for individuals undergoing therapy.

(3) A highly integrated system can provide better user experience in wearability and functionality.

5. Conclusion

Researchers have collaborated to implement IMU-based Mocap systems in the field of rehabilitation, with a focus on three dimensions: rehabilitation application, target population, and system deployment and measurement. The most commonly studied application was performance assessment, whereas rehabilitation training received relatively less emphasis. Pathological conditions such as neuro-disease and musculoskeletal disease, in which stroke being the most frequently analyzed, were the main target populations. Additionally, non-pathological rehabilitation, with a focus on gait analysis, was also widely analyzed. Regarding system deployment and measurement, the statistical data showed that lower-limb gait analysis using two IMUs to measure spatio-temporal parameters was the most commonly studied. However, the limitation of sensor drift and low battery life has resulted in a lack of precise motion analysis of the upper limb and long-term training applications. To address these limitations, we propose a potential solution from two perspectives. First, the trend of developing power-efficient chips or lower-consumption transmission methods has been on the rise for long-term therapy. Second, sensor fusion is being used to create multi-modal systems that minimize sensor errors and provide additional information.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We acknowledge the funding supports from Shenzhen Science and Technology Program (JCYJ20220530113811027, JCYJ20220818103602004, and JCYJ20210324104203010), Shenzhen Key Laboratory of Smart Healthcare Engineering (ZDSYS20200811144003009), the National Key Research and Development Program of China (2022YFF1202500, 2022YFF1202502), and the Funds for the Cultivation of Guangdong College Students' Scientific and Technological Innovation, China ("Climbing Program" Special Funds, pdjh2023c11305), and College Students' Innovative Entrepreneurial Training Plan Program, China (Y01381868).

Appendix. Abbreviations

Mocap	Motion capture
IMU	Inertial measurement unit
OMC	Optical motion capture
ADL	Activities of daily living
MEMS	Micro-electro-mechanical system
AR	Augmented reality
RNN	Recurrent neural network
STP	Spatiotemporal parameter
CoM	Center of mass
SA	Symmetry angle
JA	Joint angle
GMM	Gaussian mixture model
INS	Inertial navigation system
EMG	Electromyography
MTMM-DTW	Multitemplate multi-match dynamic time warping
FPA	Foot progression angle
MMG	Mechanomyography
POF	Polymer optical fiber
SVM	Support vector machine
THA	Total hip arthroplasty
ACL	Anterior cruciate ligament
RoM	Range of motion
SCI	Spinal cord injury
PD	Parkinson's disease
PRISMA	Preferred reporting items for systematic reviews and meta-analysis

References

[1] A. Cieza, K. Causey, K. Kamenov, S.W. Hanson, S. Chatterji, T. Vos, Global estimates of the need for rehabilitation based on the global burden of disease study 2019: A systematic analysis for the global burden of disease study 2019, Lancet 396 (10267) (2020) 2006–2017, http://dx.doi.org/10.1016/S0140-6736(20)32340-0.

[2] G..W.H. Organization, Rehabilitation 2030 initiative, 2017, URL https://www.who.int/initiatives/rehabilitation-2030.

[3] I.D. Alliance, Advancing the rights of persons with disabilities, 2022, URL https://www.internationaldisabilityalliance.org/.

[4] F. Horak, L. King, M. Mancini, Role of body-worn movement monitor technology for balance and gait rehabilitation, Phys. Ther. 95 (3) (2015) 461–470, http://dx.doi.org/10.2522/ptj.20140253.

[5] M. Yahya, J.A. Shah, K.A. Kadir, Z.M. Yusof, S. Khan, A. Warsi, Motion capture sensing techniques used in human upper limb motion: A review, Sens. Rev. 39 (4) (2019) 504–511, http://dx.doi.org/10.1108/SR-10-2018-0270, 10/gf3t45.

[6] R.A.W. Felius, M. Geerars, S.M. Bruijn, J.H. van Dieën, N.C. Wouda, M. Punt, Reliability of imu-based gait assessment in clinical stroke rehabilitation, Sensors 22 (3) (2022) http://dx.doi.org/10.3390/s22030908, https://www.mdpi.com/1424-8220/22/3/908.

[7] A.A.A. Timmermans, H.A.M. Seelen, R.P.J. Geers, P.K. Saini, S. Winter, J. te Vrugt, H. Kingma, Sensor-based arm skill training in chronic stroke patients: Results on treatment outcome, patient motivation, and system usability, IEEE Trans. Neural Syst. Rehabil. Eng. 18 (3) (2010) 284–292, http://dx.doi.org/10.1109/TNSRE.2010.2047608.

[8] E. Digo, S. Pastorelli, L. Gastaldi, A narrative review on wearable inertial sensors for human motion tracking in industrial scenarios, Robotics 11 (6) (2022) http://dx.doi.org/10.3390/robotics11060138, https://www.mdpi.com/2218-6581/11/6/138.

[9] C.P. Walmsley, S.A. Williams, T. Grisbrook, C. Elliott, C. Imms, A. Campbell, Measurement of upper limb range of motion using wearable sensors: A systematic review, Sports Med. - Open 4 (1) (2018) 53, http://dx.doi.org/10.1186/s40798-018-0167-7.

[10] S. Díaz, J. Stephenson, M. Labrador, Use of wearable sensor technology in gait, balance, and range of motion analysis, Appl. Sci. (Switzerland) 10 (1) (2020) http://dx.doi.org/10.3390/app10010234.

[11] A.C. Alarcón-Aldana, M. Callejas-Cuervo, A.P.L. Bo, Upper limb physical rehabilitation using serious videogames and motion capture systems: A systematic review, Sensors (Basel, Switzerland) 20 (21) (2020) http://dx.doi.org/10.3390/s20215989.

[12] J. Figueiredo, J. Moreno, A. Matias, F. Pereira, C. Santos, Outcome measures and motion capture systems for assessing lower limb orthosis-based interventions after stroke: A systematic review, Disabil. Rehabilitat Assist. Technol. 16 (6) (2021) 674–683, http://dx.doi.org/10.1080/17483107.2019.1695966.

[13] E. Knippenberg, J. Verbrugghe, I. Lamers, S. Palmaers, A. Timmermans, A. Spooren, Markerless motion capture systems as training device in neurological rehabilitation: A systematic review of their use, application, target population and efficacy, J. NeuroEng. Rehabil. 14 (1) (2017) 61, http://dx.doi.org/10.1186/s12984-017-0270-x.

[14] Q. Wang, P. Markopoulos, B. Yu, W. Chen, A. Timmermans, Interactive wearable systems for upper body rehabilitation: A systematic review, J. NeuroEng. Rehabil. 14 (1) (2017) 20, http://dx.doi.org/10.1186/s12984-017-0229-y.

[15] F. Porciuncula, A.V. Roto, D. Kumar, I. Davis, S. Roy, C.J. Walsh, L.N. Awad, Wearable movement sensors for rehabilitation: A focused review of technological and clinical advances, Pm R 10 (9) (2018) S220–S232.

[16] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, PRISMA Group*, Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement, Ann. Internal Med. 151 (4) (2009) 264–269, http://dx.doi.org/10.7326/0003-4819-151-4-200908180-00135.

[17] P. Slade, A. Habib, J.L. Hicks, S.L. Delp, An open-source and wearable system for measuring 3D human motion in real-time, IEEE Trans. Biomed. Eng. 69 (2) (2022) 678–688, http://dx.doi.org/10.1109/TBME.2021.3103201.

[18] S. Zhang, F. Naghdy, D. Stirling, M. Ros, A. Gray, Ankle injury assessment using inertial 3D data, in: 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, IEEE, Wollongong, NSW, 2013, pp. 810–815, http://dx.doi.org/10.1109/AIM.2013.6584193.

[19] M. Zecca, K. Saito, S. Sessa, L. Bartolomeo, Z. Lin, S. Cosentino, H. Ishii, T. Ikai, A. Takanishi, Use of an ultra-miniaturized IMU-based motion capture system for objective evaluation and assessment of walking skills, in: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE, Osaka, 2013, pp. 4883–4886, http://dx.doi.org/10.1109/EMBC.2013.6610642.

[20] A. Yurtman, B. Barshan, Automated evaluation of physical therapy exercises using multi-template dynamic time warping on wearable sensor signals, Comput. Methods Programs Biomed. 117 (2) (2014) 189–207, http://dx.doi.org/10.1016/j.cmpb.2014.07.003.

[21] W.W. Lee, S.-C. Yen, E.B.A. Tay, Z. Zhao, T.M. Xu, K.K. Mui Ling, Y.-S. Ng, E. Chew, A.L.K. Cheong, G.K.C. Huat, A smartphone-centric system for the range of motion assessment in stroke patients, IEEE J. Biomed. Health Inf. 18 (6) (2014) 1839–1847, http://dx.doi.org/10.1109/JBHI.2014.2301449.

[22] A.H. Moreira, S. Queiros, J. Fonseca, P.L. Rodrigues, N.F. Rodrigues, J.L. Vilaca, Real-time hand tracking for rehabilitation and character animation, in: 2014 IEEE 3nd International Conference on Serious Games and Applications for Health, SeGAH, IEEE, Rio de Janeiro, 2014, pp. 1–8, http://dx.doi.org/10.1109/SeGAH.2014.7067086.

[23] I. Carpinella, D. Cattaneo, M. Ferrarin, Quantitative assessment of upper limb motor function in multiple sclerosis using an instrumented action research arm test, J. NeuroEng. Rehabil. 11 (1) (2014) 67, http://dx.doi.org/10.1186/1743-0003-11-67.

[24] E. Papi, D. Osei-Kuffour, Y.-M.A. Chen, A.H. McGregor, Use of wearable technology for performance assessment: A validation study, Med. Eng. Phys. 37 (7) (2015) 698–704, http://dx.doi.org/10.1016/j.medengphy.2015.03.017.

[25] F.B. van Meulen, J. Reenalda, J.H. Buurke, P.H. Veltink, Assessment of daily-life reaching performance after stroke, Ann. Biomed. Eng. 43 (2) (2015) 478–486, http://dx.doi.org/10.1007/s10439-014-1198-y.

[26] S. Tedesco, A. Urru, A. Clifford, B. O'Flynn, Experimental validation of the tyndall portable lower-limb analysis system with wearable inertial sensors, Procedia Eng. 147 (2016) 208–213, http://dx.doi.org/10.1016/j.proeng.2016.06.215.

[27] J. Li, B. Pan, T. Jin, Z. Huang, S. Ye, J. Wu, Z. Huang, B. Xie, C. Luo, C. Wang, A single task assessment system of upper-limb motor function after stroke, Technol. Health Care 24 (s2) (2016) S707–S715, http://dx.doi.org/10.3233/THC-161199.

[28] F.S. Ayachi, H.P. Nguyen, C. Lavigne-Pelletier, E. Goubault, P. Boissy, C. Duval, Wavelet-based algorithm for auto-detection of daily living activities of older adults captured by multiple inertial measurement units (IMUs), Physiol. Meas. 37 (3) (2016) 442–461, http://dx.doi.org/10.1088/0967-3334/37/3/442.

[29] H. Zhao, Z. Wang, S. Qiu, Y. Shen, J. Wang, IMU-based gait analysis for rehabilitation assessment of patients with gait disorders, in: 2017 4th International Conference on Systems and Informatics, ICSAI, IEEE, Hangzhou, 2017, pp. 622–626, http://dx.doi.org/10.1109/ICSAI.2017.8248364.

[30] X. Zhang, L. Xu, Y. Zhang, A wireless evaluation system for in-home physical rehabilitation, in: 2017 29th Chinese Control and Decision Conference, CCDC, IEEE, Chongqing, China, 2017, pp. 3375–3380, http://dx.doi.org/10.1109/CCDC.2017.7979089.

[31] J. Xu, U.H. Lee, T. Bao, Y. Huang, K.H. Sienko, P.B. Shull, Wearable sensing and haptic feedback research platform for gait retraining, in: 2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks, BSN, IEEE, Eindhoven, Netherlands, 2017, pp. 125–128, http://dx.doi.org/10.1109/BSN.2017.7936023.

[32] R.B. Woodward, S.J. Shefelbine, R. Vaidyanathan, Pervasive monitoring of motion and muscle activation: Inertial and mechanomyography fusion, IEEE/ASME Trans. Mechatronics 22 (5) (2017) 2022–2033, http://dx.doi.org/10.1109/TMECH.2017.2715163.

[33] F. Visi, T. Georgiou, S. Holland, O. Pinzone, G. Donaldson, J. Tetley, Assessing the accuracy of an algorithm for the estimation of spatial gait parameters using inertial measurement units: Application to healthy subject and hemiparetic stroke survivor, in: Proceedings of the 4th International Conference on Movement Computing, ACM, London United Kingdom, 2017, pp. 1–7, http://dx.doi.org/10.1145/3077981.3078034.

[34] E. Villeneuve, W. Harwin, W. Holderbaum, B. Janko, R.S. Sherratt, Reconstruction of angular kinematics from Wrist-Worn inertial sensor data for smart home healthcare, IEEE Access 5 (2017) 2351–2363, http://dx.doi.org/10.1109/ACCESS.2016.2640559.

[35] M. Valtin, C. Salchow, T. Seel, D. Laidig, T. Schauer, Modular finger and hand motion capturing system based on inertial and magnetic sensors, Curr. Dir. Biomed. Eng. 3 (1) (2017) 19–23, http://dx.doi.org/10.1515/cdbme-2017-0005.

[36] R. Ranganathan, R. Wang, B. Dong, S. Biswas, Identifying compensatory movement patterns in the upper extremity using a wearable sensor system, Physiol. Meas. 38 (12) (2017) 2222–2234, http://dx.doi.org/10.1088/1361-6579/aa9835.

[37] M. Delrobaei, N. Baktash, G. Gilmore, K. McIsaac, M. Jog, Using wearable technology to generate objective Parkinson's disease Dyskinesia severity score: possibilities for home monitoring, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (10) (2017) 1853–1863, http://dx.doi.org/10.1109/TNSRE.2017.2690578.

[38] C. Yi, N. Ma, C. Yang, H. Guo, J. Han, H. Gao, X. Li, F. Jiang, A novel automatic diagnosis based physical therapy for Duchenne muscular dystrophy children, in: 2018 IEEE Third International Conference on Data Science in Cyberspace, DSC, IEEE, Guangzhou, 2018, pp. 547–552, http://dx.doi.org/10.1109/DSC.2018.00088.

[39] L. Wang, Y. Sun, Q. Li, T. Liu, Estimation of step length and gait asymmetry using wearable inertial sensors, IEEE Sens. J. 18 (9) (2018) 3844–3851, http://dx.doi.org/10.1109/JSEN.2018.2815700.

[40] P. Kutilek, A.C.D.M. de Brito, J. Hejda, E. Kutilkova, P. Volf, B. Adamova, V. Havlas, Methods of motion assessment of upper limb for rehabilitation application, in: 2018 International Conference on Applied Electronics, AE, IEEE, Pilsen, 2018, pp. 1–4, http://dx.doi.org/10.23919/AE.2018.8501423.

[41] A. Karatsidis, R.E. Richards, J.M. Konrath, J.C. van den Noort, H.M. Schepers, G. Bellusci, J. Harlaar, P.H. Veltink, Validation of wearable visual feedback for retraining foot progression angle using inertial sensors and an augmented reality headset, J. NeuroEng. Rehabil. 15 (1) (2018) 78, http://dx.doi.org/10.1186/s12984-018-0419-2.

[42] J.P.O. Held, B. Klaassen, A. Eenhoorn, B.-J.F. van Beijnum, J.H. Buurke, P.H. Veltink, A.R. Luft, Inertial sensor measurements of upper-limb kinematics in stroke patients in clinic and home environment, Front. Bioeng. Biotechnol. 6 (2018) 27, http://dx.doi.org/10.3389/fbioe.2018.00027.

[43] N. England, S. Islam, H. Licht, A. Sarris, C. Twigg, Sensor embedded knee sleeve for post-operative ACL patients, in: 2018 Systems and Information Engineering Design Symposium, SIEDS, IEEE, Charlottesville, VA, 2018, pp. 165–170, http://dx.doi.org/10.1109/SIEDS.2018.8374729.

[44] S. Sharif Bidabadi, I. Murray, G.Y.F. Lee, Validation of foot pitch angle estimation using inertial measurement unit against marker-based optical 3D motion capture system, Biomed. Eng. Lett. 8 (3) (2018) 283–290, http://dx.doi.org/10.1007/s13534-018-0072-5.

[45] Teufl, Taetz, Miezal, Lorenz, Pietschmann, Jöllenbeck, Fröhlich, Bleser, Towards an inertial sensor-based wearable feedback system for patients after total hip arthroplasty: Validity and applicability for gait classification with gait kinematics-based features, Sensors 19 (22) (2019) 5006, http://dx.doi.org/10.3390/s19225006.

[46] J. Marín, T. Blanco, J.J. Marín, A. Moreno, E. Martitegui, J.C. Aragüés, Integrating a gait analysis test in hospital rehabilitation: A service design approach, in: A. Soundy (Ed.), PLOS ONE 14 (10) (2019) e0224409, http://dx.doi.org/10.1371/journal.pone.0224409.

[47] X. Liu, S. Rajan, N. Ramasarma, P. Bonato, S.I. Lee, The use of a finger-worn accelerometer for monitoring of hand use in ambulatory settings, IEEE J. Biomed. Health Inf. 23 (2) (2019) 599–606, http://dx.doi.org/10.1109/JBHI.2018.2821136.

[48] B.-S. Lin, I.-J. Lee, P.-Y. Chiang, S.-Y. Huang, C.-W. Peng, A modular data glove system for finger and hand motion capture based on inertial sensors, J. Med. Biol. Eng. 39 (4) (2019) 532–540, http://dx.doi.org/10.1007/s40846-018-0434-6.

[49] N. Lefeber, M. Degelaen, C. Truyers, I. Safin, D. Beckwee, Validity and reproducibility of inertial physilog sensors for spatiotemporal gait analysis in patients with stroke, IEEE Trans. Neural Syst. Rehabil. Eng. 27 (9) (2019) 1865–1874, http://dx.doi.org/10.1109/TNSRE.2019.2930751.

[50] J. Konrath, A. Karatsidis, H. Schepers, G. Bellusci, M. de Zee, M. Andersen, Estimation of the knee adduction moment and joint contact force during daily living activities using inertial motion capture, Sensors 19 (7) (2019) 1681, http://dx.doi.org/10.3390/s19071681.

[51] M.E. Kayaalp, A.N. Agres, J. Reichmann, M. Bashkuev, G.N. Duda, R. Becker, Validation of a novel device for the knee monitoring of orthopaedic patients, Sensors 19 (23) (2019) 5193, http://dx.doi.org/10.3390/s19235193.

[52] K.H. Beange, A.D. Chan, S.M. Beaudette, R.B. Graham, Concurrent validity of a wearable IMU for objective assessments of functional movement quality and control of the Lumbar spine, J. Biomech. 97 (2019) 109356, http://dx.doi.org/10.1016/j.jbiomech.2019.109356.

[53] I. Weygers, M. Kok, H. De Vroey, T. Verbeerst, M. Versteyhe, H. Hallez, K. Claeys, Drift-free inertial sensor-based joint kinematics for long-term arbitrary movements, IEEE Sens. J. 20 (14) (2020) 7969–7979, http://dx.doi.org/10.1109/JSEN.2020.2982459.

[54] E. Warmerdam, R. Romijnders, J. Welzel, C. Hansen, G. Schmidt, W. Maetzler, Quantification of arm swing during walking in healthy adults and Parkinson's disease patients: Wearable sensor-based algorithm development and validation, Sensors 20 (20) (2020) 5963, http://dx.doi.org/10.3390/s20205963.

[55] V.D. Tsakanikas, D. Gatsios, D. Dimopoulos, A. Pardalis, M. Pavlou, M.B. Liston, D.I. Fotiadis, Evaluating the performance of balance physiotherapy exercises using a sensory platform: sthe basis for a persuasive balance rehabilitation virtual coaching system, Front. Digit. Health 2 (2020) 545885, http://dx.doi.org/10.3389/fdgth.2020.545885.

[56] S.Y. Shin, R.K. Lee, P. Spicer, J. Sulzer, Quantifying dosage of physical therapy using lower body kinematics: A longitudinal pilot study on early post-stroke individuals, J. NeuroEng. Rehabil. 17 (1) (2020) 15, http://dx.doi.org/10.1186/s12984-020-0655-0.

[57] A. RajKumar, F. Vulpi, S.R. Bethi, H.K. Wazir, P. Raghavan, V. Kapila, Wearable inertial sensors for range of motion assessment, IEEE Sens. J. 20 (7) (2020) 3777–3787, http://dx.doi.org/10.1109/JSEN.2019.2960320.

[58] S. Qiu, H. Wang, J. Li, H. Zhao, Z. Wang, J. Wang, Q. Wang, D. Plettemeier, M. Bärhold, T. Bauer, B. Ru, Towards wearable-inertial-sensor-based gait posture evaluation for subjects with unbalanced gaits, Sensors 20 (4) (2020) 1193, http://dx.doi.org/10.3390/s20041193.

[59] J. Marin, J.J. Marin, T. Blanco, J. de la Torre, I. Salcedo, E. Martitegui, Is my patient improving? individualized gait analysis in rehabilitation, Appl. Sci. 10 (23) (2020) 8558, http://dx.doi.org/10.3390/app10238558.

[60] Y. Hutabarat, D. Owaki, M. Hayashibe, Quantitative gait assessment with feature-rich diversity using two IMU sensors, IEEE Trans. Med. Robot. Bionics 2 (4) (2020) 639–648, http://dx.doi.org/10.1109/TMRB.2020.3021132.

[61] L. De Baets, S. Vanbrabant, C. Dierickx, R. van der Straaten, A. Timmermans, Assessment of scapulothoracic, glenohumeral, and elbow motion in adhesive capsulitis by means of inertial sensor technology: A within-session, intra-operator and inter-operator reliability and agreement study, Sensors 20 (3) (2020) 876, http://dx.doi.org/10.3390/s20030876.

[62] I. Aranda-Valera, A. Cuesta-Vargas, J. Garrido-Castro, P. Gardiner, C. López-Medina, P. Machado, J. Condell, J. Connolly, J. Williams, K. Muñoz-Esquivel, T. O'Dwyer, M. Castro-Villegas, C. González-Navas, E. Collantes-Estévez, on behalf of iMaxSpA Study Group, Measuring spinal mobility using an inertial measurement unit system: A validation study in axial spondyloarthritis, Diagnostics 10 (6) (2020) 426, http://dx.doi.org/10.3390/diagnostics10060426.

[63] C. Werner, C. Awai Easthope, A. Curt, L. Demkó, Towards a mobile gait analysis for patients with a spinal cord injury: A robust algorithm validated for slow walking speeds, Sensors 21 (21) (2021) 7381, http://dx.doi.org/10.3390/s21217381.

[64] L. Wang, Y. Sun, Q. Li, T. Liu, J. Yi, IMU-based gait normalcy index calculation for clinical evaluation of impaired gait, IEEE J. Biomed. Health Inf. 25 (1) (2021) 3–12, http://dx.doi.org/10.1109/JBHI.2020.2982978.

[65] L.S. Vargas-Valencia, F.B.A. Schneider, A.G. Leal-Junior, P. Caicedo-Rodriguez, W.A. Sierra-Arevalo, L.E. Rodriguez-Cheu, T. Bastos-Filho, A. Frizera-Neto, Sleeve for knee angle monitoring: an IMU-POF sensor fusion system, IEEE J. Biomed. Health Inf. 25 (2) (2021) 465–474, http://dx.doi.org/10.1109/JBHI.2020.2988360.

[66] O. Tsilomitrou, K. Gkountas, N. Evangeliou, E. Dermatas, Wireless motion capture system for upper limb rehabilitation, Appl. Syst. Innov. 4 (1) (2021) 14, http://dx.doi.org/10.3390/asi4010014.

[67] N. Schlage, A. Kitzig, G. Stockmanns, E. Naroska, Development of a mobile, cost-effective and easy to use inertial motion capture system for monitoring in rehabilitation applications, Curr. Dir. Biomed. Eng. 7 (2) (2021) 586–589, http://dx.doi.org/10.1515/cdbme-2021-2149.

[68] S.M. Parker, J. Crenshaw, N.H. Hunt, C. Burcal, B.A. Knarr, Outdoor walking exhibits peak ankle and knee flexion differences compared to fixed and adaptive-speed treadmills in older adults, BioMed. Eng. OnLine 20 (1) (2021) 104, http://dx.doi.org/10.1186/s12938-021-00941-0.

[69] C. Monoli, J.F. Fuentez-Perez, N. Cau, P. Capodaglio, M. Galli, J.A. Tuhtan, Land and underwater gait analysis using wearable IMU, IEEE Sens. J. 21 (9) (2021) 11192–11202, http://dx.doi.org/10.1109/JSEN.2021.3061623.

[70] T.-H. Hwang, A.O. Effenberg, Head trajectory diagrams for gait symmetry analysis using a single head-worn IMU, Sensors 21 (19) (2021) 6621, http://dx.doi.org/10.3390/s21196621.

[71] Y. Hou, S. Wang, J. Li, S. Komal, K. Li, Reliability and validity of a wearable inertial sensor system for gait assessment in healthy Young adults, in: 2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI, IEEE, Shanghai, China, 2021, pp. 1–6, http://dx.doi.org/10.1109/CISP-BMEI53629.2021.9624463.

[72] B. Fan, H. Xia, J. Xu, Q. Li, P.B. Shull, IMU-based knee flexion, abduction and internal rotation estimation during drop landing and cutting tasks, J. Biomech. 124 (2021) 110549, http://dx.doi.org/10.1016/j.jbiomech.2021.110549.

[73] S. Di Paolo, N.F. Lopomo, F. Della Villa, G. Paolini, G. Figari, L. Bragonzoni, A. Grassi, S. Zaffagnini, Rehabilitation and return to sport assessment after anterior cruciate ligament injury: quantifying joint kinematics during complex high-speed tasks through wearable sensors, Sensors 21 (7) (2021) 2331, http://dx.doi.org/10.3390/s21072331.

[74] P. Arens, C. Siviy, J. Bae, D.K. Choe, N. Karavas, T. Baker, T.D. Ellis, L.N. Awad, C.J. Walsh, Real-time gait metric estimation for everyday gait training with wearable devices in people poststroke, Wearable Technol. 2 (2021) e2, http://dx.doi.org/10.1017/wtc.2020.11.

[75] G. Patel, R. Mullerpatan, B. Agarwal, T. Shetty, R. Ojha, J. Shaikh-Mohammed, S. Sujatha, Validation of wearable inertial sensor-based gait analysis system for measurement of spatiotemporal parameters and lower extremity joint kinematics in sagittal plane, Proc. Inst. Mech. Eng. Part H: J. Eng. Med. 236 (5) (2022) 686–696, http://dx.doi.org/10.1177/09544119211072971.

[76] C. Mittag, V. Waldheim, A. Krause, T. Seel, Using a single inertial sensor to control exergames for children with Cerebral Palsy, Curr. Dir. Biomed. Eng. 8 (2) (2022) 431–434, http://dx.doi.org/10.1515/cdbme-2022-1110.

[77] R. Mallat, V. Bonnet, M.A. Khalil, S. Mohammed, Upper limbs kinematics estimation using affordable visual-inertial sensors, IEEE Trans. Autom. Sci. Eng. 19 (1) (2022) 207–217, http://dx.doi.org/10.1109/TASE.2020.3024033.

[78] J. Li, X. Liu, Z. Wang, X. Zhou, Z. Wang, Sensor combination selection for human gait phase segmentation based on lower limb motion capture with body sensor network, IEEE Trans. Instrum. Meas. 71 (2022) http://dx.doi.org/10.1109/TIM.2022.3201947.

[79] J. Sung, S. Han, H. Park, H.-M. Cho, S. Hwang, J.W. Park, I. Youn, Prediction of lower extremity multi-joint angles during overground walking by using a single IMU with a low frequency based on an LSTM recurrent neural network, Sensors 22 (1) (2022) http://dx.doi.org/10.3390/s22010053.

[80] J. Camargo, D. Molinaro, A. Young, Predicting biological joint moment during multiple ambulation tasks, J. Biomech. 134 (2022) http://dx.doi.org/10.1016/j.jbiomech.2022.111020.

[81] Z. Gu, S. Liu, S. Cosentino, A. Takanishi, Development of a non-contacting muscular activity measurement system for evaluating knee extensors training in real-time, Sensors 22 (12) (2022) http://dx.doi.org/10.3390/s22124632.

[82] S. Tedesco, O.M. Torre, M. Belcastro, P. Torchia, D. Alfieri, L. Khokhlova, S.D. Komaris, B. O'Flynn, Design of a multi-sensors wearable platform for remote monitoring of knee rehabilitation, IEEE Access Pract. Innov. Open Solut. 10 (2022) 98309–98328, http://dx.doi.org/10.1109/ACCESS.2022.3204969.

[83] J.F.S. Lin, D. Kulić, Human pose recovery using wireless inertial measurement units, Physiol. Meas. 33 (12) (2012) 2099–2115, http://dx.doi.org/10.1088/0967-3334/33/12/2099.

[84] A. Spooren, Y. Janssen-Potten, E. Kerckhofs, H. Bongers, H. Seelen, ToCUEST: A task-oriented client-centered training module to improve upper extremity skilled performance in cervical spinal cord-injured persons, Spinal Cord 49 (10) (2011) 1042–1048.

[85] P. Page, Current concepts in muscle stretching for exercise and rehabilitation, Int. J. Sports Phys. Therapy 7 (1) (2012) 109.