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IMU-based systems for upper limb kinematic analysis in clinical applications: a systematic review

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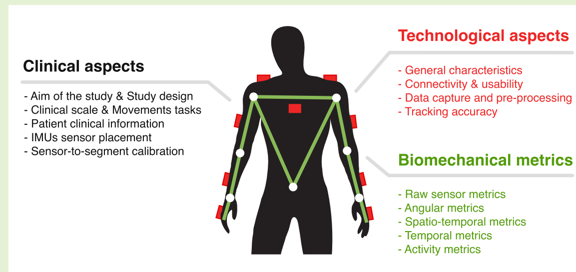
***Abstract*— Wearable inertial sensors have undergone great development offering an easy approach to track physical activity for both athletes and for the general public. Their immense potential to assess motion impairment in clinical practice is now fostering research on evaluation protocols, sensor configurations, and significant metrics that could be helpful to evaluate the condition of patients with a motor disease. This systematic review provides a clear picture of the current state-of-art in this research area, outlining the dominant trends, promising opportunities for future work and some guidelines to pursue them. We review Inertial Measurement Unit-based systems that have been used to assess upper limb kinematics in people with acquired neurological disease and neuromuscular disease, over the last 20 years. We evaluate the technological characteristics of the sensors and the clinical contexts in which they have been applied. Finally, we study the biomechanical metrics analyzed in the reviewed papers, focusing on those with clinical relevance to assess and evaluate the motor status of the patients.**



***Index Terms*— Clinical environment, home-setting, Inertial Measurement Unit (IMU), neurological disease, neuromuscular disease, upper limb**

I. Introduction

MOTION disorders, due to muscular dystrophy or neurological disease, often result in long-term motor disabilities that hinder the performance of daily living activities, thus drastically impacting the quality of life of patients, their families and caregivers. Recently there have been promising advances in therapies for these diseases, which call for the development of technological tools and methodologies to evaluate the response of individual patients to such new treatments. Currently, the degree of motion impairment is assessed through the application of motor functional scales by a physiotherapist in a clinical environment, without any technological help. This assessment method has some limitations, such as a possible learning effect, reduced repeatability, and difficulty to detect relevant changes in slowly progressing diseases. Standardized measurment of the motor function of patients in real-life conditions is increasingly required in order to properly assess the patients' baseline condition and their response to therapies.

Looking for technologies to help with such standardized measurement, human motion analysis stands out as a well-established research field that aims at gathering quantitative information about the mechanics of the musculo-skeletal system during the execution of a motor task [1]. This field of study encompasses a variety of techniques with multiple applications, ranging from surveillance systems to the evaluation of athletic performance and medical diagnosis [2]. Visual-based techniques have the longest tradition, whereby color and/or depth cameras are used to record video, from which human motion is extracted. Another video-based technique widely used nowadays is optical motion capture, which relies on infrared cameras that track markers placed on the skin. Nevertheless, Inertial Measurement Units (IMUs), i.e., electronic devices that track movement of the body part where they are attached, are quickly gaining popularity because of their small size, light weight and the possibility of being used outside the laboratory [3].

An IMU consists of an accelerometer and a gyroscope, providing linear acceleration and angular velocity, respectively, which combined yield the orientation of the attachment [4]. Since both accelerometer and gyroscope measurements suffer from time-dependent biases and noises, the use of IMUs is affected by drift problems caused by the integration of those signals over time. The most recent sensor models include

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a magnetometer that, measuring the earth's magnetic field, improves the estimation of the IMU orientation, limiting the drift [5], [6]. Due to environmental magnetic disturbances, the use of the magnetometer is occasionally not possible. In this case, the drift can be minimized by using correction algorithms [7]–[9].

Data acquired by an optical motion capture system is often considered the gold-standard, against which the performance of IMUs is experimentally tested [10]. A lot of work has been done to prove the validity of inertial-based systems to obtain the kinematics of the lower and upper limbs, demonstrating good precision, fast applicability and accuracy [11]–[14]. Not surprisingly, IMUs have attracted the attention of physiotherapists and bioengineers, as they open up the possibility of a quantitative and objective characterization of a patient's functional state, both in clinical and home environments, thus complementing the use of scales and questionnaires to overcome some of their limitations [15].

Literature reviews have already acknowledged the importance and the potential of IMU-based systems for motion analysis. Nevertheless, some previous reviews focused on the use of IMUs without considering their clinical application and the challenges that can arise in such context [16], [17]. Others narrowed their analyses to only one specific motor disorder, such as cerebral palsy [18], stroke [19], Duchenne muscular dystrophy [20] or multiple sclerosis [21]. Finally, one review considered the potential benefits and drawbacks of using wearable sensors to assess motor disorders caused by neurological diseases [22], without including muscular dystrophies nor focusing on their clinical application.

The aim of this review is to provide an overview of the use of IMU-based motion capture equipment in the clinical field, focusing on the kinematic analysis of the upper limb movement in people affected by a motor disorder caused by a neurological or neuromuscular disease. Therefore, we seek to answer the following research questions:

1. What clinical protocols are used to evaluate upper limb kinematics in people with motor disorder using IMU-based systems?
2. What are the technical characteristics and configurations of inertial sensors that are most suitable for clinical application?
3. What biomechanical metrics obtained from IMU-based systems are useful for clinical practice?

II. Materials and Methods

A. Search Strategy

We looked for scientific articles published between 2000 and March 2023 in four online databases, using the following search terms: ((wearable OR "inertial motion unit* OR "inertial movement unit*" OR "inertial measurement unit*" OR "inertial sensor*" OR "magneto-inertial") AND ("movement* analysis" OR "motion analysis*" OR "motion track*" OR "track* motion*" OR "motor function assessment" OR "human joint measurement" OR "limb movement "OR "measurement system*" OR "limb activity") AND ("upper limb*" OR arm OR arms OR elbow* OR wrist* OR shoulder*OR hand*) AND ("neuromuscular" OR "neurologic*"OR "clinical "OR "disease")). The online databases considered were PubMed, Web of Science, Scopus and IEEE Xplore. We found a total of 687 articles: 66 in IEEE Xplore, 93 in PubMed, 197 in Web of Science and 331 in Scopus.

After removing 244 duplicates, 443 publications were analyzed based on their title and abstract, and 80 publications were full-text assessed for eligibility. The research, screening and eligibility check of the studies were all done by the same two authors (i.e. Alessandra Favata and Roger Gallart-Agut). In case of indecision, consensus was reached collaboratively among all authors of the manuscript. Finally, 34 articles were included in this review. The PRISMA flow diagram, presented in Fig. 1, the analysis perfomed at each stage of the screening process, where n represents the number of articles.

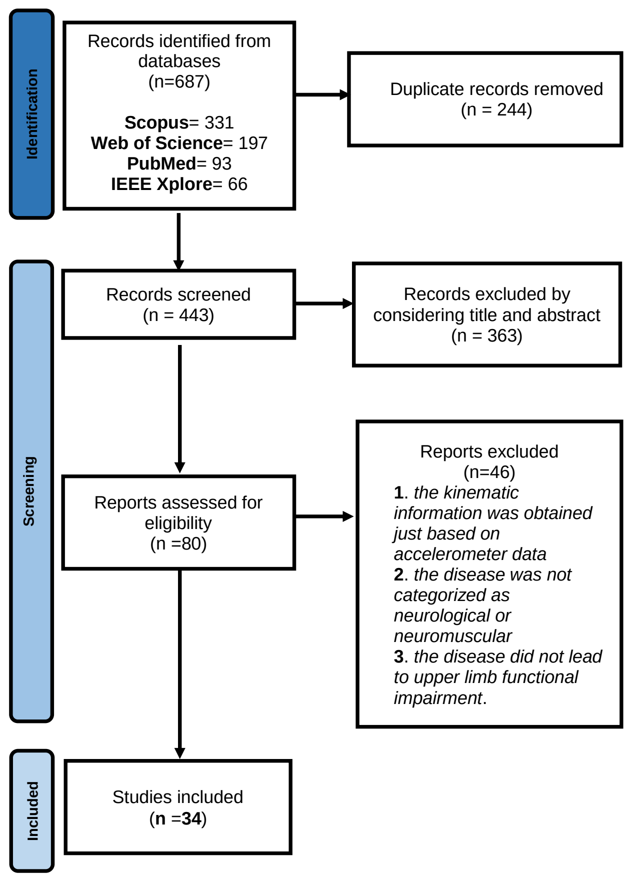

Fig. 1. Flow diagram of the screening process according to PRISMA guidelines.

B. Inclusion and exclusion criteria

We only included publications written in English, which provided relevant information aimed on studying the use of inertial motion capture systems and their application in the clinical field, focusing on upper limb kinematic analysis.

To be included in the review, each article had to meet the following conditions: (1) at least one IMU had to be used

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to assess upper limb kinematics, (2) the IMUs had to be equipped at least with a 3-axis accelerometer and a 3-axis gyroscope, (3) the inertial system had to be used in a clinical application, (4) the study had to involve at least one participant with a neurological or neuromuscular disease and (5) the study had to be a journal article. All the studies were approved by the local Ethics Committees. Studies were excluded based on the following criteria: (1) the kinematic information was obtained just based on accelerometer data, (2) the disease was not categorized as neurological or neuromuscular, or (3) the disease did not lead to upper limb functional impairment.

C. Approach

The information of each study was classified according to the clinical aspects (i.e., study design and protocol design), technical aspects (i.e., data pre-processing), and biomechanical metrics.

In the Clinical Aspects section, we analyzed the information regarding the patients involved in the studies and the protocol (tasks movement, sensor placement and sensor-to-segment calibration) implemented to perform the kinematic analysis. The subjects involved in the studies were categorized according to age, disease and sample size. The sensor placement was described according to the number of inertial sensors used and the considered body segments. The studies were classified into four groups according to their type of study: (1) experimental validation (experimental preliminary evaluation of the device), (2) pilot study (small-scale test of the methods or procedure), (3) observational study (study in which individuals are observed or certain outcomes are measured. i.e., descriptive study, cohort study, longitudinal study, cross-sectional study, or pre-post study), and (4) experimental study (researchers introduce an intervention and study the effects, i.e., randomised control trial) [23].

In the Technical Aspects section, the sensors were classified based on their main characteristics (i.e. wired/wireless or with/without magnetometer, sampling frequency) that have to be considered in the clinical practice. We also analyzed the type of processing data algorithm used for the kinematic analysis of the upper limb movement. In particularly, we analyzed the filter and algorithm to limit the errors in the acceleration and gyroscope data. Fig. 2 shows the main steps to obtain kinematic information starting from the data coming from the accelerometer, gyroscope and magnetometer.

Lastly, in the Biomechanical Metrics section, we categorized the main outcome metrics of the kinematic analysis and examined their potential correlation with disease progression. We classified these metrics in five main groups: raw sensor metrics (raw data obtained directly from accelerometer and gyroscope), angular metrics, spatio-temporal metrics, temporal metrics, and activity metrics.

III. Clinical Aspects

This section reviews the main clinical aspects related to the studies included. We will focus our analysis on the demographic analysis (age and disease) and clinical protocol (clinical or home setting, purpose of the study, number of IMUs, and body segment evaluated). Table I provides a summary of the details covered in this subsection. The flowchart illustrated in Fig. 3 summarizes the main aspects to consider when using IMU-based systems for upper-limb kinematic analysis.

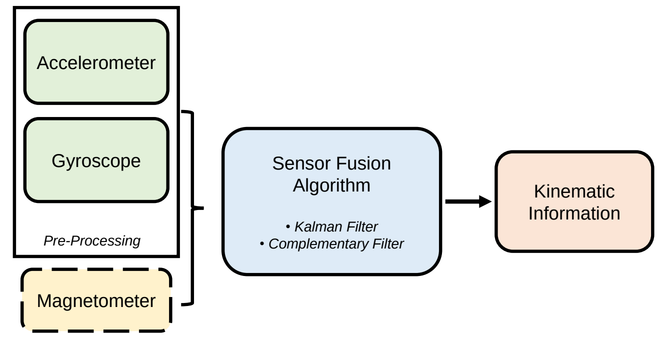

Fig. 2. Work flow diagram to obtain kinematic information from IMU measurements. The data coming from the 3-axis accelerometer and 3-axis gyroscope are processed in order to reduce the errors and drift. A sensor fusion algorithm (Kalman filter or Complementary filter) is then used to merge the information from the accelerometer, gyroscope and magnetometer (when present). From those data it is possible to obtain kinematic information.

A. Aim of the study and Study design

Table I, Column 2, shows a detailed list outlining the objectives of the reviewed studies. Due to their compact size, user-friendliness, and suitability for use outside the laboratory, IMUs have found extensive application in monitoring and tracking human movement, including various clinical scenarios [24]. Clinicians are becoming more interested in monitoring the patients during their daily life. Analyzing data from real-life conditions might help improve the assessment of patients' level of independence and eventually increase their quality of life. In this context, IMUs can help to obtain quantitative information of everyday life motor activities [25]. We found that the vast majority of the analyzed works (n = 32, 94.1%) aimed to find relevant parameters to quantitatively characterize the motor disease using an IMU-based system. Within this majority, all studies found at least one kinematic parameter that was useful to assess the motor status of the patient. Furthermore, two works (5.88%) aimed to demonstrate that home therapy using an IMU-based system is safe and can also provide rehabilitative training [26], [27].

Eighteen studies (52.9%) aimed to quantitatively characterize the motor disease with an IMU-based system while the subjects are performing the clinical scale. The majority of these works found at least one kinematic parameter, obtained with the IMU-based system, that showed a good correlation with the clinical score, demonstrating the validity of the system. Even when correlation was not detected, authors explained that the metrics obtained with the IMUs offered valuable insights that would have otherwise been difficult to detect solely by the clinicians. This indicates the potential capability of the system to offer complementary information. Interestingly, eight works (23.5%) asked the patients to perform tasks related to daily

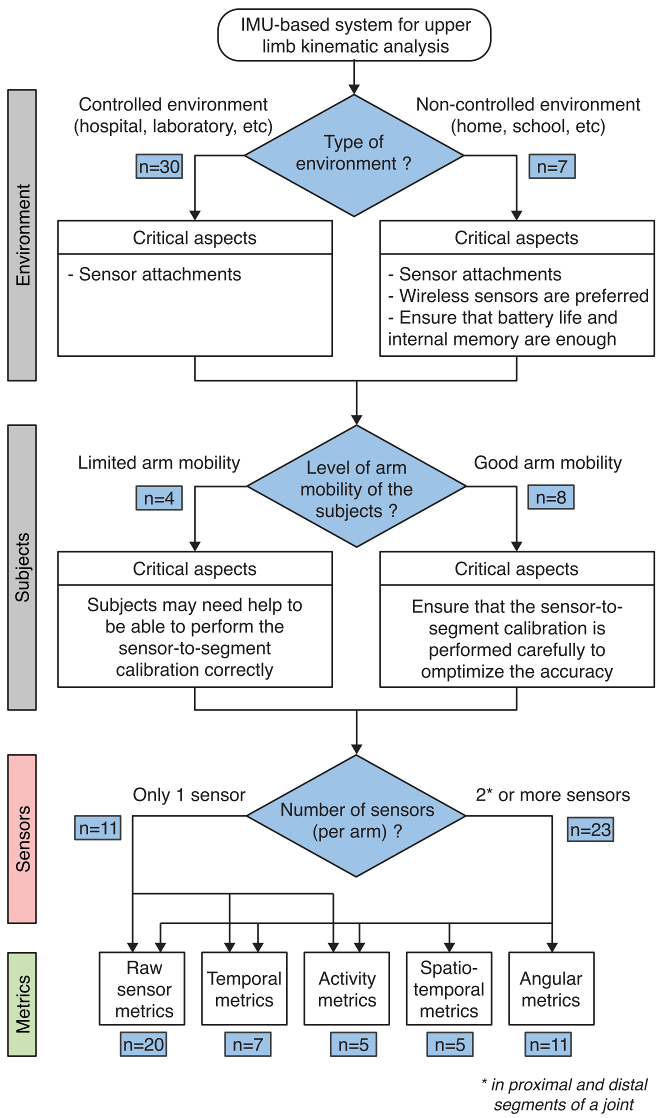

Fig. 3. Flowchart to design an IMU-based system for upper-limb kinematic analysis.

life activities, demonstrating the increasing interest to bridge the gap between subjective clinical motor assessments and quantitative kinematic analysis of the upper limb movements during daily life [41]. Among these movements, reaching for an object stands out as the most commonly requested one. This trend can be attributed to the movement's comprehensive exploration of the upper limb's overall function and to its fundamental role in the daily life. Gaining insight into its dynamics could significantly contribute to improving the rehabilitation process [35], [42], [43]. See Table I Column 4 for more information about the clinical scale and the movement tasks analyzed in the reviewed articles.

Six works (17.6%) recorded the data in a home environment to collect information about the actual upper-limb use during daily living [28]–[33]. IMU-based systems can give information on arm movements in a home environment, overcoming the limitations related with the clinical environment (e.g., shorter periods and objectivity) [28], [35].

These findings show a growing interest and effort to incorporate IMU-based measurement systems into daily life activities to acquire more insightful information about motor diseases [28]–[30], [32], [34], [35]. Moreover, IMUs offer the advantage of capturing kinematic parameters, such as spatio-temporal parameters, which are challenging to quantify through standard clinical observation alone. Those data can provide a deeper insight of the upper limb use in natural settings, helping the clinician to better tailor the intervention.

The aim of the study influences the study design and it serves as a guide to the research approach. Among the four groups of studies mentioned in Section II-C, the observational study (n = 20, 58.8%) represented the most frequent study design among the selected works, followed by pilot study (n = 7, 20.6%), experimental study (n = 6, 17.6%), and experimental validation (n = 1, 2.9%). The reduced number of experimental studies may be attributed to the relatively recent interest in utilizing inertial systems for analyzing the kinematics of the upper body. Fig. 4 provides a distribution of the four study types according to the year of publication. Since 2015, there has been an average annual publication of three to four articles on IMU-based systems for the upper-limb kinematic analysis, reaching a peak in 2021. This coincided with the post-pandemic period, demonstrating a constant interest in IMU-based systems for clinical applications over recent years. Table I, Column 2, includes a comprehensive guide, offering insights into the objectives and methodologies of each study. This categorization not only enhances the comprehension of each study's goals but also categorizes them based on their research methodologies, enabling a deeper understanding of the various approaches employed in the field.

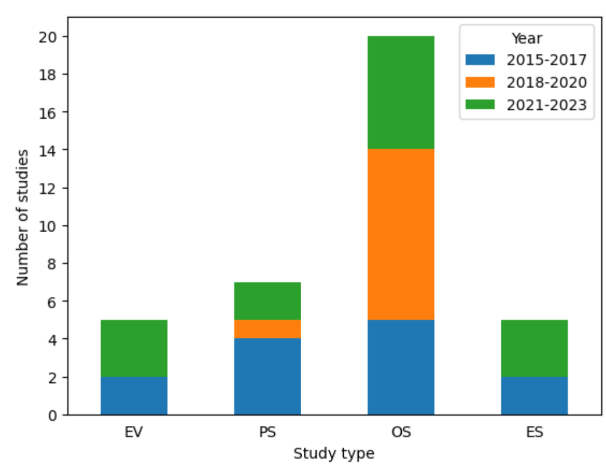

Fig. 4. Number of publications by year and type of study. The types of study are: experimental validation (EV), pilot study (PS), observational study (OS), and experimental study (ES).

B. Patient Clinical Information

Table I, Column 3, shows a detailed list of the patients clinical information. The average number of participants in the included studies was 26.1, ranging from a minimum of 1 participant in [44] to 140 participants in [45]. Only 3 studies analyzed patients with age below 18 years old, defined as children. The rest of the studies involved adults over 18 years old. Three studies recruited a group of people involving both children and adults, ranging from 5 years old to 30 years old.

Fig. 5 represents the percentage of the pathologies analyzed in the studies. Stroke, one of the leading causes of disability worldwide, was the most studied disease (n = 16, 47.0%) [46]. The second one was Parkinson disease (PD) (n = 8, 23.5%), followed by Spinal Cord Injury (SCI) (n = 3, 8.8%). Just a few works focused on diseases that affect people during early life, like Duchenne Muscular Dystrophy (DMD) (n = 1, 2.9%), Spinal Muscular Atrophy (SMA)(n = 1, 2.9%), or Cerebral Palsy (CP) (n = 5, 14.7 %).

Throughout the examined studies, it is clear that IMUs can be applied across a broad age range, to both children and adults, as well as in the assessment of different motor diseases. This underscores the versatility of IMUs, highlighting their suitability for various subjects.

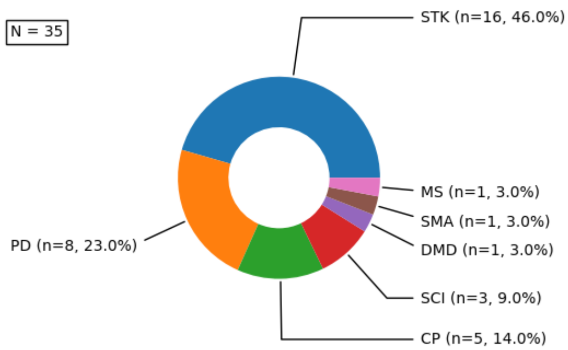

Fig. 5. Number of studies by disease type: Stroke (STK), Parkinson Disease (PD), Cerebral Palsy (CP), Spinal Cord Injury (SCI), Duchenne Muscular Dystrophy (DMD), Spinal Muscular Atrophy (SMA) and Multiple Sclerosis (MS). *The works total number is 35: Newman et al. [35] conducted analyses on both children with Stroke and with Cerebral Palsy.

C. IMUs Sensor Placement

In this section we categorized the reviewed articles according to the number of IMUs used, the body segments to which each IMU was attached, and the position of the IMU within the segment (i.e., closer to the proximal or the distal joint). The body segments have been defined according to the criteria described in [47]. The number of sensors comprises a single side of the upper body (i.e., the torso and a single arm) even when the article used a symmetric bilateral sensor setup. For example, if an article described a setup with 7 sensors in the upper body with 3 sensors in each arm and 1 sensor in the torso, in this review it is considered as a system of 4 IMUs. Fig. 6 shows the relation between the studied diseases and the number of IMUs used. Fig. 7 summarizes the body segments and locations where the IMUs are placed in the reviewed studies. This representation offers a clear overview of the sensors placement strategies employed in the works reviewed.

Eleven different studies (32.3%) analyzed the movement of the upper body using a single IMU. In ten of these works

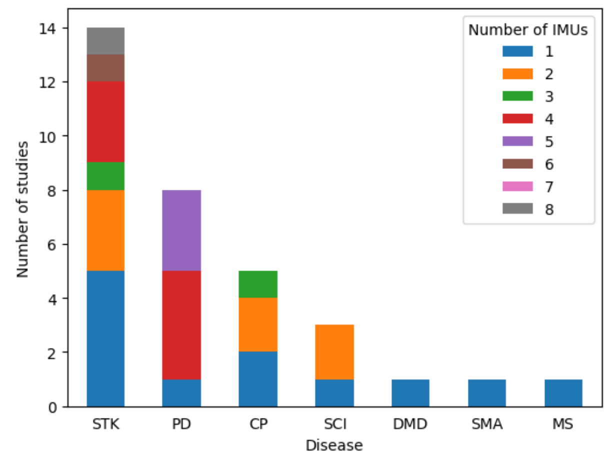

Fig. 6. Number of studies by disease and number of IMUs used. Diseases: Stroke (STK), Parkinson Disease (PD), Cerebral Palsy (CP), Spinal Cord Injury (SCI), Duchenne Muscular Dystrophy (DMD), Spinal Muscular Atrophy (SMA) and Multiple Sclerosis (MS). *The works total number is 35: [35] conducted analyzes on both children with stroke and with Cerebral Palsy.

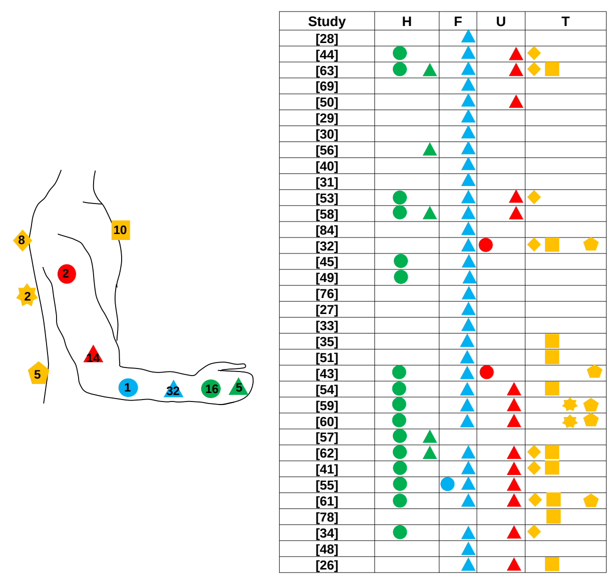

Fig. 7. Lateral view of the upper limb body part. Four body segments are analyzed: hand (green), forearm (blue), upper arm (red) and torso (yellow) . The position of the IMU is also shown: proximal (circle), distal (triangle), square (sternum level), rhombus (shoulder level), star (middle back) and pentagon (waist level). Inside the shapes are shown the number of works that analyze the body segment. * [49] utilized one IMU but with two different placements.

(29.4%), the IMU was placed on the forearm, at the wrist level. As shown in Fig. 7, this placement was the most commonly utilized and this tendency could be associated with the characteristics of wrist-worn sensors, which allow to capture movement quality metrics, such as peak velocity and trajectory smoothness [48]. In just one case (2.9%), the sensor was placed on the hand [49]. Interestingly, this study employed two different configurations tailored to two different tests: Finger-to-Nose Test and Dysdiadochokinesia Test. In the former, the sensor was attached to the subject's dorsal surface of the hand and, while in the latter, the sensor was attached at wrist level. Just one work (2.9%) used a single IMU attached to the torso, at the sternum level, to enhance the understanding of trunk control in children with CP. Overall, employing a single IMU in a protocol offers the advantage of simplifying the measurement system, resulting in reduced setup time and user inconvenience [44].

Six studies (17.6%) analyzed the kinematics of the upper body part using two IMUs, considering this setup as a viable option due to its simple implementation and ability in providing valuable data [29], [33], [35], [45], [50], [51]. It should also be underlined that a minimum of two IMUs in consecutive segments is required to build a kinematic model and obtain the kinematic information of the corresponding joint. In that regard, only Oubre et al. placed the sensors in two non-consecutive body segments. In [51], the authors placed the sensors on the forearm and the torso, using the IMU on the torso as reference, to subsequently extract kinematic features from the IMU placed on the wrist. Khaksar et al. encountered a specific issue when the sensors placed on the hand and forearm came into contact due to the participants' small hands, resulting in increased noise [45]. In that regard, Wirth et al. propose maintaining a minimum distance of 3 cm between forearm and hand sensors during the capture process to mitigate these issues [52].

Eight works (23.5%) analyzed the kinematics of the upper limb with four IMUs. Four studies analyzed the same body segments (torso, upper arm, forearm and hand), but placing the sensor on the torso at different heights [43], [44], [53], [54]. Serrano et al. placed one IMU on the upper arm, two on the forearm (at elbow and wrist level), and one on the hand [55]. Lastly, Cavallo et al., and Rovini et al., employed the same wearable system (SensHand) with one IMU on the forearm and three more on the hand, on the distal phalanges of the thumb, index and middle finger [56] [57]. The wide array of sensor configurations underscores the versatility and flexibility of IMUs in capturing upper limb kinematics in various research settings.

Five works (14.7%) implemented a configuration with five IMUs. Di Biase at al. analyze the upper arm, the forearm and the hand, placing 3 IMUs on the hand and 1 IMU on each of the other segments [58]. The IMUs on the hand were placed on the index finger, distal phalanx of the thumb and the metacarpus because the authors wanted to identify the best placement where to locate sensors. Their findings revealed that a distal location, such as on the index finger, is preferred for capturing kinematic characteristics specific to Parkinson's patients. Moreover, Held et al., recorded the data with a 14 IMU-based system full-body motion capture system, even if only five sensors were used to analyze the upper limb. These five were placed on the forearm, upper arm, and torso. In this case, according to the authors, the setup was obtrusive and not suitable for long-term recording [32].

One work (2.9%) used 6 IMUs to analyze the upper limb kinematics [61]. The authors used a full-body motion capture system with sensors placed on hand, forearm, upper arm and torso. In this work, authors stated that the high number of sensors, the cables and the straps may have had an impact on the movements exhibited of the patients under study.

The analyzed system with the highest number of sensors placed on the upper limb (8 IMUs) is developed by Schwarz et al., and Bhagubai et al. [62] [63]. In both cases, the body segments analyzed were 4: torso (with IMUs at sternum level and on the scapula), upper arm, forearm and hand (with one IMU on the dorsal side of the hand and three on the fingers).

It can be concluded that, a setup with just one sensor allows the subject to move more freely and, at the same time, to collect data about that specific body segment. This is for instance the case of the IMUs placed on the wrist that are easily attached to the forearm with a watch-like band. However, the limitation of a single-IMU setup lies in the necessity of using two or more sensors to construct a kinematic chain. Even in setups with only two sensors, the information gathered remains restricted to just one joint. Finally, using a system with at least three IMUs enables the assessment of the inter-joint kinematics (relationship among one ore more joints), enhancing the precision of the upper body kinematics evaluation and improving the overall accuracy of the assessment.

D. Sensor-to-segment Calibration

A proper calibration of the IMUs is necessary to establish the relation between the sensor coordinate system and the corresponding human segment on which it is placed [64]. Four categories of sensor-to-segment calibration methods have been described in the literature [65]: (1) Assumed Alignment (AA) Method: manually aligning the IMU's axes with the segment axes; (2) Functional Alignment (FA) Method: aligning IMU's axes based on subjects' known movement(s) or pose(s); (3) Model Based (MB) Method: estimating body segment anatomical axes using either a kinematic model or a statistical model of the joint; and (4) Augmented Data (AD) Method: using information from another source (e.g. optical motion capture) to determine the relationship between the IMU's frame and the body segment frame. Many studies have been working on developing efficient calibration methods for the upper body in healthy subjects. However, in the case of people affected by a motor disease who are incapable of performing a functional or pre-determined pose, the methods described above could be difficult to implement [66].

In this review, seven works (20.6%) employed a FA method. In three studies (8.8%), the sensor-to-segment calibration method used was based on performing just a static pose [26], [40], [44]. In the other four works (11.8%), the setup calibration was performed not only with a static pose but also including functional movements (e.g. abduction and flexion movements) to enhance the accuracy of the calibration [35], [41], [62], [63]. In all these cases, the clinicians had to help the patients to perform the calibration movement. For one work (2.9%), the calibration procedure consisted in standing in a neutral position and walking for a few meters, as explained in the user manual of the manufacturer [41].

Unfortunately, the majority of the studies (n=27, 79.4%) do not clearly describe the procedure followed to perform the sensor-to-segment calibration, even if it is crucial to estimate

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the body segment orientations and each sensor-to-segment calibration can lead to different results [67].

IV. Technological Aspects

This section analyzes the main technical features of the inertial sensors used in the included studies. We describe the components of the different IMUs and the algorithms implemented to process the measured data. We also specify which sensors are available on the market and which are not. See Table II, Column 2, to have more information regarding the type of sensor used in the reviewed studies.

A. General characteristics

Twenty-one of the works reviewed (61.8%) opted to use commercial devices, while twelve (35.3%) used prototypes or custom self-built devices (one work did not mention the IMU used). Among the commercial brands, the most used was Xsens (n=7, 20,6%), followed by Shimmer Research, Sysnav and Captiks (with n=2, 5,9% for each brand).

Using commercial wearable IMUs greatly simplifies data collection as they undergo thorough testings and quality controls during their production. This typically makes them more robust and reliable,compared to self-built devices. Commercial IMUs also offer additional off-the-shelf advantages to researchers, by either supplying the orientation of the sensor in form of quaternions or Euler angles (along with the raw inertial data) or providing a post-processing software with a biomechanical model. Some researchers may choose to implement their own sensor fusion algorithm and pre-processing techniques rather than using the ones supplied by the device manufacturer [16]. It is important to remark that there also exist IMU modules that greatly simplify the process of designing and building a custom wearable sensor [43], [45], [49].

All the studies included in the review used IMUs equipped with a 3-axis accelerometer and a 3-axis gyroscope to measure the linear acceleration and angular velocity, respectively. Eighteen works (52.9%) made use of IMUs with a magnetometer, while fifteen works (44.1%) either chose a device without a magnetometer or simply did not use it. The magnetometer provides the orientation relative to the Earth's magnetic field, which can be used to correct the data drift; however, magnetic measurements are sensitive to magnetic field disturbances [68]. Most of the reviewed works using IMUs with magnetometer (n=17, 50.0%) did not report any issues related to magnetic interference; but it is worth taking into account that twelve of them (35.3%) were being used in a controlled environment and for relatively short periods of time, which reduces the chances of disturbances. Just one study (2.9%) addressed problems with the environmental factors (i.e., electronic devices at home) [32].

Based on this evidence, it appears that researchers might prefer to use commercial sensors because of their robust algorithm to process the data collected (i.e., the fusion algorithm). As for the magnetometer's presence, drawing a definitive conclusion is challenging; the majority of studies using a magnetometer have been conducted in controlled environments, requiring further analysis for conclusive insights.

B. Connectivity and usability

The wearable IMU systems used in the reviewed articles can be grouped in two main categories: (1) wired systems and (2) wireless systems. Wired systems usually consist of a set of small IMUs placed on the body and physically connected with cables to a hub device, which is usually located on the back or the waist of the patient [53], [55], [61]. This hub device is responsible for collecting and pre-processing all the data, as well as supplying power to the sensors. These centralized systems enable smaller sensor units, without power supplies or communication systems, providing battery autonomy and processing capabilities. However, the wires connecting sensors to the hub and the size of the hub itself can be cumbersome, restricting these systems to short captures in controlled environments. Sometimes the cables are integrated into a suit to increase the comfort and mobility. This type of architecture is also common when monitoring the movement of the fingers, with the hub located at the wrist level [56], [57].

On the contrary, wireless systems consist in a set of independent sensors that can be controlled wirelessly from a host device [28], [50], [69]. This hardware setup requires each IMU device to integrate at least a microcontroller, a connectivity module (e.g., Bluetooth or radiofrequency), an internal memory storage (e.g., microSD or SSD) and a rechargeable battery. These systems tend to be more comfortable for the patients, particularly in non-controlled environments and during daily live activities; but they remain more limited in terms of autonomy and processing power. Nevertheless, the improvement in wireless communication protocols (e.g., BLE Bluetooth Low-Energy) and battery technologies are increasing the autonomy of such systems.

One crucial point, especially when dealing with long-term motion capture in uncontrolled environments, is to reduce as much as possible the movement of the sensors with respect to the body segment to which they are attached [70]. Only sixteen (47.1%) of the reviewed articles explicitly mention the method used to attach the sensors to the body. Some of the most referenced ways to attach the sensors to the upper limbs are Velcro® straps [41], [44], [60], [61], silicone straps [33], and elastic bands [59]. Some authors reported the use of medical tape to attach the sensors to the body as an alternative to straps [41], [62], [63]. Lastly, for the shoulder and sternum sensors, VanMeulen et al. chose a small unobtrusive harness [61].

Ensuring the comfort of the user while wearing the sensors is also important to get reliable results and long-term adherence to the technology. Bai et al. added under the Velcro® strap a piece of Velfoam®, a foam covered with hook-sensitive material on one side and nylon on the reverse side, to reduce the discomfort of sensor attachment and minimize the relative movement of the sensors with respect to the limb [44]. VanMeulen et al. instructed patients to walk around before recording data to adjust strapping and wiring to not obstruct their natural movements [61]. Lee et al. performed a survey among several stakeholders to gather feedback with the objective of identifying the most comfortable wristband mechanism

[27]. Two types of slap bracelets have been identified as the easiest to be worn for the self-application to the wrist.

C. Data capture and pre-processing

When the magnetometer is absent, the orientation of the sensor is based solely on the data coming from the accelerometer and the gyroscope. However, accelerometer and gyroscope data are prone to errors [31], [44]. The accelerometer might be affected by vibration and rapid movement, while a small offset in measured angular velocity results in increasing inaccuracy in the estimated orientation [71] [64]. To overcome these issues, common practices involve applying low-pass filtering to the acceleration data, while algorithms like the zero-velocity update (ZUPT) are employed to reduce angular velocity drift. The ZUPT algorithm is commonly used in gait analysis and relies on accurately identifying intervals of zero velocity, which may not easily recognized for general upper limb movements. However, for certain upper limb assessment tests, specific events are known when limb segments remain stationary, allowing the ZUPT algorithm to be effectively applied. Bhagubai et al. and Schwarz et al. considered the sensors stationary when the angular velocity was lower than a threshold (e.g., 3 deg/s) [62], [63]. The other authors asked the subjects to perform repetitive tasks, allowing them to use the algorithm step-by-step (similar to a gait analysis).

Lastly, a sensor fusion algorithm is used to merge the information from the accelerometer, the gyroscope and the magnetometer (when present) to obtain the sensor orientation. The sensor fusion algorithms implemented in the reviewed studies can be grouped in two main classes: (1) Kalman filter (KF); and (2) Complementary filter (CF), e.g., Madgwick (MAD) and Mahony (MAH) filters [72]–[74]. The KF estimates the error following a prediction-correction scheme, while the CF combines the information from two or more sources (e.g., accelerometer and gyroscope) [9], [75]. Eight of the reviewed studies (23.5%) implemented the Kalman filter [32], [40], [44], [48], [51], [54], [76], while eight studies (23.5%) used complementary filters as a sensor fusion algorithm [26], [31], [33], [50], [62], [63]. Seven of these studies used a Madgwick filter (MAD). This filter showed a higher accuracy compared to other common sensor fusion algorithms like the Kalman filter, but with less computational load [77]. Unfortunately, the majority of the analyzed works (n=21, 61.8%) did not report the type of sensor fusion algorithm implemented to obtain the orientation of the sensors.

Only twenty-one of the reviewed works (61.8 %) mention the sampling frequency used, which ranges from 20 Hz to 256 Hz, with 50Hz being the most common one (n=9, 26.5%). It is worth nothing that depending on the article and on the type of device used, this value might refer either to the sampling rate used to capture the data by a component (i.e., gyroscope, accelerometer or magnetometer) or to the output rate of the pre-processed data supplied to the user. In wireless systems, the maximum output rate allowed might be limited by the wireless communication bandwidth or by the internal memory storage, among others. For instance, in the Xsens MTw used by Oubre et al. and VanWonterghem et al. the data from the accelerometer and gyroscope are captured at a sampling frequency of 1000 Hz and internally low-pass filtered at a bandwidth of 184 Hz [51], [78]. Then, the user can choose an output rate whose maximum value is limited by the number of sensors used. However, the minimum sampling frequency needed to record upper-limb motion in individuals with neuromuscular disorders is relatively low, as their capacity for rapid movements is often restricted. Indeed, a few of the reviewed articles (see Table II) indicate that inertial data were low-pass filtered using cut-off frequencies between 5 Hz and 12 Hz for general movement analysis, and between 15 Hz and 20 Hz for tremor analysis.

D. Tracking Accuracy

In IMU-based motion tracking, accuracy has generally been quantified by comparison with an optical system, considered the gold standard because of its high measurement precision in position [52]. Generally, the quantities reported are root mean squared error (RMSE), correlation coefficients and Bland-Altman limits of agreement [14], [79].

Six of the reviewed articles (17.6%) evaluated the accuracy of the IMU-based system used [44], [35], [45], [59]- [61]. Bai et al. analyzed the error of position tracking, reporting an error of 2 mm and a 99% correlation between the IMU-based system and the optoelectronic system [44]. VanMeulen et al. evaluated the differences in hand-reaching distances using both systems [61]. The mean error recorded was up to 35 mm, with a standard deviation of 34 mm, with higher errors in higher reaching distances. The authors suggest that these differences are due to the incapacity of the IMU sensors to fully track the shoulder protraction and retraction, and the trunk movements during these tasks. The other articles reported an average error of 1.80° with respect to the gold standard, when evaluating shoulder angles during a standard task (i.e., abduction and elevation) [35]. Lastly, in one case, the accuracy of the system was assessed by comparing the peak angles using wearable sensors with those obtained using a robotic device in the sagittal plane (i.e., flexion/extension), reporting a mean error ranging from -2.63° to 0.54°, at high speed (90°/s). Mean errors ranging from -0.92° to 2.90° were observed at lower speed (30°/s) [45]. Generally, these findings indicate that the data accuracy of IMU-based systems is sufficient for monitoring the kinematics of the upper limbs in individuals with motor impairments. Despite certain limitations, especially in reaching tasks, exist, these systems have proven to be a valuable equipment for evaluating and comprehending upper-limb motion in both clinical and research contexts. Ongoing enhancements and adjustments may further improve their efficacy across a range of applications.

V. Biomechanical Metrics

All the reviewed articles analyzed the kinematics of the upper body part. It is possible to group the kinematic outcome metrics into five main categories: raw metrics, spatio-temporal metrics, angular metrics, temporal metrics and activity metrics. All the reported parameters have shown clinical meaning and importance related to the disease analyzed. In the next

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sections, we discuss how these metrics can be related with the clinical practice. In Fig. 8 we show the relationship between the biomechanical metrics and the analyzed diseases.

A. Raw sensor metrics

Raw sensor metrics are features directly obtained from the gyroscope (i.e., angular velocity) and accelerometer (i.e., linear acceleration) data, typically after some pre-processing to reduce noise and drift (see section IV-C). These are the most straightforward metrics to work with as they do not require any biomechanical model and can be obtained even with a single IMU. Among the studies reviewed, several authors implemented raw sensor metrics combined with machine learning techniques to classify between healthy subjects and patients [40], [45], [49], [56], [57], [59]; to predict the clinical score of patients undergoing an assessment scale [48], [51]; and to identify activities of daily living (ADL) in patients with tremor [55], [69].

Each IMU sensor generates six time-series (for 3-axes gyroscopes and 3-axes accelerometers). Additional time-series can be derived by calculating the first and second derivatives of the angular velocity (angular acceleration and angular jerk) and the first derivative of the linear acceleration (jerk). A large variety of features can be obtained by analyzing these data either in the time domain or the frequency domain. Typical time domain features include minimum/maximum values, mean, median, standard deviation, percentiles, root mean square value (RMS), skewness and kurtosis. Other features can be obtained in the frequency domain from the power spectral density (PSD) of the signal, such as the total power, the power in a specific frequency band or the amplitude and phase shift of specific harmonics.

Eight works (23.5%) analyzed the angular velocity, collected through the IMU's gyroscope, to evaluate the upper limb motor control [28], [34], [35], [58]–[60], [76], [78]. LeMoing et al. found that the angular velocity obtained from a wrist-worn sensor in children with DMD could be a promising metric to assess their upper limb motor function [76]. Vanmechelen et al. and VanWonterghem et al. analyzed children with CP during a reaching task and observed higher values of the angular velocity,compared to a control group [34], [78]. The authors linked these results to a motor pattern characterized by poor control and involuntary movements.

DiBiase et al. obtained the total power from PSD of the angular velocity [58]. The authors found out that by analyzing an arm prono-supination in a group of PD, they were able to distinguish between PD with and without medication, and PD and healthy subjects, based on the total power analysis. The total power is able to catch the progressive reduction in speed and amplitude that characterizes PD during repetitive movements. For this reason, it represents a good candidate to monitor PD motor symptoms. Ricci et al. analyzed a group of PD subjects and obtained different features related to the angular velocity (i.e., peaks, variation of amplitude), known indicators of rhythm and asymmetry of movement, which are characteristics of the analyzed disease [59], [60]. In [59], they analyzed a *de novo* group not influenced by any therapeutic intervention, with respect to a group of healthy subjects. In [60], they analyzed a group of PD patients treated with a pharmacological therapy. In the first case, those features have been found to be significantly different in PD compared to healthy subjects, demonstrating to be relevant to assess the motor status of the patient. The second work confirms this result demonstrating that these features are able to track the change of the therapy. Compared with the clinical score of the UPDRS, these features showed partial accordance. However, some features are not easily detectable to the examiner's eye. Those results demonstrate that using an IMU-based system may be a valid support in assessing PD in the early stage and along the therapy, helping to adjust the therapy for each patient.

Krishna et al. successfully trained a Linear Discrimant Analysis model to classify patients with cerebellar ataxia according to the disease severity, while performing two tasks, i.e., the Finger-to-Nose test (FNT) and the Dysdiadochokinesia Test (DDK) [49]. The researchers observed that during the FNT task, which is a predominantly translational movement, the frequency domain features (RF: resonant frequency and MR: magnitude of the resonant frequency) of the angular acceleration along the forearm axis gave the best classification results. On the contrary, for the DDK task, which uses predominantly rotational movements, the RF and MR features of the linear acceleration gave the best results.

Two studies (5.9%) used the angular jerk to evaluate the upper limb movement smoothness in children with CP [34] and stroke survivors [54], demonstrating that patients adopt different coordination strategies.

Four articles (11.8%) examined the linear acceleration as a way to quantify the upper limb motor function [28], [34], [76], [78]. Announssamy et al. showed that the mean value of the linear acceleration of the wrist in children with SMA, collected in an home-environment, significantly decreased after 6 and 12 months of observation. This metric could be used to track the progression of the illness [28]. VanWonterghem et al. measured the acceleration (range and peak) of the trunk in children with CP, during a reaching task, and obtained higher values in comparison to the control group, due to a poorer trunk control of the patients [78]. Similar conclusions were drawn when analyzing the peak linear acceleration of the hand, forearm and upper arm in children with CP [34].

To assess the smoothness of the movement, two papers (5.9%) evaluated the jerk, as a measure of fluency [34], [35]. Vanmechelen et al. obtained the jerk from the acceleration data of the IMUs placed on the hand, forearm and upper arm [34]. They analyzed children with CP while performing reaching tasks. In comparison to the healthy group, they revealed that children with CP had significantly higher maximal jerk, which is linked to more uncontrolled movement. Newman et al. computed the normalized jerk from the acceleration data recorded by the IMU placed on the upper arm, where the jerk metric was normalized by the maximum linear velocity [35]. They found that during a reaching task, the normalized jerk of the paretic upper arm in children with CP was higher in comparison with the non-paretic one. This variable allows to objectively quantify that the paretic limb movements were

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less fluid due to inefficient motor control. It is worth noting that no correlation was found between this variable and the MA's clinical score. However, since the authors stated that this metric might capture features of movement that the human eye cannot evaluate, its clinical relevance is not diminished [35].

It is possible to conclude that raw metrics, easily obtained directly from the sensor, are ideal candidates for machine learning analysis. Their lack of clear biomechanical interpretation can be addressed through machine learning processes, enabling the discovery of insights not easily detected in initial analyses. Additionally, these metrics provided valuable information regarding the status of patients with motor diseases.

B. Angular metrics

An effective way to evaluate the function of the upper limbs is quantifying the angular kinematics of upper body joints [80]. For instance, the Range of Motion (ROM), obtained from the joint angles might be a useful clinical outcome, as individuals may experience impaired joint mobility due to a health issue or injury [81], [82]. In this review, joint angles resulted the most analyzed variables. Thirteen studies (38.2%) calculated them to quantify the joint mobility. In [41], [43], [62], [63], the authors analyzed the angular kinematics of the upper limb in stroke survivors to quantify pathological synergies. Bhagubai et al. evaluated shoulder, elbow and wrist angles while the subjects were performing four items of the FMA clinical scale [63]. They found out that the shoulder flexion, which according to the clinical scale has to be performed with the elbow totally extended, was accompanied by involuntary shoulder abduction and elbow flexion. For both the most and less affected subjects, the joint angles were found to be closely correlated with the FMA score. In other cases, the relationship between metrics and clinical scores was unclear, possibly due to the finer grain scale of the IMU-based system compared to the discrete clinical scale (ranging from 0 to 2). Schwarz et al. analyzed the trunk angular variation and the shoulder, elbow, wrist, and fingertip ROMs since those variables were expected to describe the interjoint coordination and pathological compensation during a reaching task. The authors were able to quantify the characteristics of movement impairments and the strategies of inter-joint coordination [62]. They found that the weakness of the shoulder and the elbow muscles was compensated by a higher trunk ROM.

To quantify the relationship between shoulder and elbow kinematics and to evaluate inter-joint coordination of stroke survivors, Schwarz et al. defined a shoulder-elbow correlation coefficient [41]. A strong correlation was found between this parameter and the FMA score, suggesting that it might quantify the same characteristic of the inter-joint coordination evaluated during the clinical assessment. This parameter also showed statistical discriminability between movement of the affected upper limb with respect to the less affected side. In order to assess the upper limb motor function in stroke patients, Pan et al. measured the shoulder range of motion and the highest value of the torso's angle during a reaching task [43]. Severe loss of motor function was associated with lower ROM of the shoulder and increased torso angle. This result is further confirmed by the finding that both the torso's angle and the shoulder ROM significantly differed between the stroke and control groups.

Leunberger et al. analyzed the elevation angle of the forearm, defined as the angle of that segment with respect to the horizontal plane, recorded during 48h to assess arm functionality in a home environment [33]. The authors found out that the paretic and non-paretic forearm elevation distribution correlated with the clinical score, supporting the initial hypothesis that the elevation angle could be a clinically relevant metric of arm impairment.

Repnik et al. analyzed the maximum angular value of the trunk with respect to the initial position, a parameter implemented in previous studies for clinical assessment of the motor function in stroke survivors [54]. They demonstrated how this metric might discriminate between stroke survivors and healthy participants. It is important to underline that even though the authors did not find any correlation between this parameter and the clinical outcome, its usefulness for clinical purposes was not diminished. There are aspects of the upper limb kinematics that cannot be easily determined from visual observations during a clinical assessment and, therefore, discrepancy can be registered with respect to the clinical score.

Delrobei et al. obtained the joint angles of shoulder, elbow and wrist during a repetitive pronation-supination task to evaluate the bradykinesia of a group of subjects with PD. The authors combined different angular metrics (i.e., standard deviation of the angles, angular velocity, and variability in terms of both time and amplitude) to derive a dimensionless index. These metrics have been proven to be descriptors of bradykinesia, with milder cases exhibiting consistent amplitudes and frequencies, while patients with severe bradykinesia tend to display lower and less uniform amplitudes and frequencies [53].

This analysis confirms the hypothesis that angular metrics (e.g., ROM) can quantify the degree of motor impairment in individuals with motor diseases, as evidenced by the correlation found with clinical scores. Furthermore, additional analysis is required when these metrics do not correlate with clinical scores, as they may provide valuable information not detectable through visual observation by clinicians.

C. Spatio-temporal metrics

Spatio-temporal metrics are commonly employed in the analysis of gait for both healthy individuals and patients. Nevertheless, they may also be applied for the assessment of upper limb kinematics, offering quantitative insights into the spatial positioning of joints or specific points on a body segment. A homogeneous transformation matrix can be used to solve the forward kinematics and obtain the linear joint kinematics, when the orientation of a body segment and the coordinates of a point belonging to it are known [66]. Five works (14.7%) defined a kinematic model, based on the orientation of the sensor and the segment length, and tracked the position of the IMU attached to a body segment to obtain biomechanical metrics related to the upper limb control in people with disability [32], [41], [43], [44], [61].

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Bai et al. examined the position of an IMU attached to the hand during a NHPT, with the aim of comparing the upper limb control of 10 healthy volunteers against a patient with brain disability [44]. Analyzing the position of the hand during the task, the authors found out that the healthy controls find easier to return to the center of the peg than the patient. This discovery implies that healthy subjects had better control of the upper limb than the patient during the NHPT test. In [32], [61], the authors aimed to examine the daily-life reaching performance of stroke patients through the analysis of position data obtained from an IMU attached to the hand. Specifically, the researchers monitored the position of that IMU relative to the pelvis in the transverse plane, and obtained the reaching area and workspace. Furthermore, they visualized the distribution of the hand's position in the transversal plane using a color map. These metrics proved to be effective in objectively evaluating the motor performance of stroke patients during their engagement in activities of daily living. It has to be noted that VanMeulen et al. primarily focused on daily-life reaching performance after stroke, while Held et al. examined upper-limb kinematics in stroke patients in both clinical and home environments.

Schwarz et al. analyzed the kinematics of the upper limb while the subjects were performing four different movement tasks (shoulder flexion, pointing ahead, grasp a glass and key insertion) to study the inter-joint coordination in stroke patients. They analyzed the data of the IMU placed on the trunk (attached to the sternum) to compute the trunk displacement. Their findings indicated that the trunk compensation increases with the increase of task complexity.

Only one study uses the linear velocity of a joint as a metric. Pan et al. calculated the linear velocity of the elbow to reflect its efficiency during a task and to evaluate the upper limb motor function [43]. They computed the elbow joint velocity as the first derivative of the elbow position, obtained according to the kinematic model, and calculated the peak and average speeds during a movement task. The study found significant differences on this metric between stroke and control groups, denoting a poor motor functionality. Furthermore, they observed high Spearman correlation coefficients between the elbow joint speed metric and the FMA scale, proving the validity of this metric.

In conclusion, spatio-temporal metrics offer insights into the progression of motor diseases. Moreover, they offer valuable information about upper limb control in individuals affected by such motor diseases.

D. Temporal metrics

A common kinematic parameter used to describe the degree of difficulty in performing a motor task is the duration [83]. By using motion capture systems, it is possible to analyze not only the entire duration of a movement but also its various phases [54], [84].

Six works (17.6%) analyzed temporal metrics to obtain quantitative information to assess the upper limb motor function [35], [43], [44], [54], [58], [84]. DiGiovanni et al. focused on the analysis of time variables, based on the hypothesis that the cycle time, as in the case of FNT, can be considered as a reliable quantitative outcome [84]. They discovered that, compared to healthy subjects, the FNT test done by MS patients took noticeably longer to be completed. Interestingly, they found out that the patients needed more time only during the adjusting phase (i.e., total time of the FNT, time to locate the tip of the nose). Since the test was conducted with eyes closed, the source of feedback came from the proprioception sensory system, and MS patients required longer time than healthy people for the sensory feedback to integrate. Repnik et al. analyzed a group of stroke patients during an ARAT to quantify arm functionality after a stroke. The findings demonstrated a significant association between time movement and ARAT score, enabling a quantitative and objective distinction between patients with various motor functions [54].

In a group of children with CP, Newman et al. examined the duration of a reaching task, since it was previously used to quantify the arm usage. By analyzing the task's duration, they discovered a statistically significant difference between the paretic and the non-paretic arm. The authors also found a good correlation between the duration and the MA score, demonstrating that the movement's duration might be considered as a global marker of movement performance [35].

Bai et al. studied the kinematics of a stroke survivor, measuring the time required to complete a NHPT and compared it with a healthy group. The test required less time in the case of the healthy subject, inferring that this metric presents a good correlation with the motor control of the upper limb [44].

DiBiase et al. calculated the total time needed, by subjects with PD to complete two tasks, finger-tapping and prono-supination, to quantify the characteristic slowness of voluntary movement of patients with PD. This metric is able to discriminate not only PD subjects with and without medication, but also PD without medication and healthy subjects [58].

Based on this evidence, it appears that time metrics are good indicators to assess the motor function of patients with motor disease. In fact, in general the authors found that patients required more time, with respect to healthy subjects, to complete the same tasks.

E. Activity Metrics

Quantifying information about the upper limb motor activity during the everyday life could help clinicians in monitoring progress and evaluating the effectiveness of the treatment, thereby overcoming the limitations of the standard clinical assessment (i.e., fluctuations in patient sympotoms over time) [25]. Six works (17.6%) focused on activity metrics to evaluate and assess arm use and functionality in a home environment.

Three works (8.8%) analyzed the activity count (AC), obtained from accelerometer data of the sensor placed on the forearm at wrist level, to estimate daily arm use [29], [30], [33]. Leuenberger et al. recorded the kinematics of stroke survivors for 48h to quantitatively assess the arm use in their home environment. They found out that the AC of the 2-day recording had a strong correlation with stroke survivors' clinical scale (BBT) scores [33]. To obtain a more accurate result, they excluded the walking phase from the study, which was measured by another sensor placed on the shank.

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Brogioli et al. analyzed the AC during a 3-day recording in a group of SCI patients to monitor their independence in a home environment [30]. A significant correlation between the AC and the clinical scale used to assess daily activity was found, demonstrating the reliability of the IMU to evaluate upper limb activity outside of the clinical setting. Therefore, the use of IMUs can provide a quantitative analysis of the functionality of the upper limb outside the controlled environment, providing novel insights into overall performance. Brogioli et al. also evaluated the limb activity of SCI patients for 3-6 hours during their daily routine. They analyzed the ”activity laterality” defined as the ratio between the ACs of the right and left upper limbs [29]. The activity laterality correlated with the score of the clinical scale used to quantify independence in a SCI patient. This finding suggests that the more one side is affected compared to the other, the less independent the patient is in daily life.

Two studies (5.9%) examined the Gross Movement score (GM), a binary score based on forearm orientation, implemented to evaluate functional arm use [31], [33]. The IMU data collected at the wrist level was used to calculate the score. The arm movement is counted (GM=1) if it occurs within a range of functional movements (i.e., threshold of 30º for the angle defined by the forearm axis and the horizontal plane). They compared the GM against the results of the BBT, clinical scale sensitive to arm and hand function, which is usually implemented to evaluate gross dexterity. Leuenberger et al. identified a significant correlation between the GM score and the BBT score, suggesting that the former may provide insights into the performance of stroke patients, both in clinical and home environments [33].

Based on the position of the hand, one work (2.9%) obtained the reaching counts of the hand (counts of the hand displacements of more than 10 cm away from the resting hand position). Held et al. compared this parameter and the FMA's clinical score at different time-points (every 2 weeks for one month), and observed a difference between the reaching counts and the score. The parameter showed an increase over time while the clinical score remained constant, demonstrating that this metric might provide supplementary information to the traditional clinical evaluation [32].

To conclude that activity metrics yield findings that are not only clinically helpful, but might provide additional information about the long-term evolution of patients during recovery and their independence in a home environment.

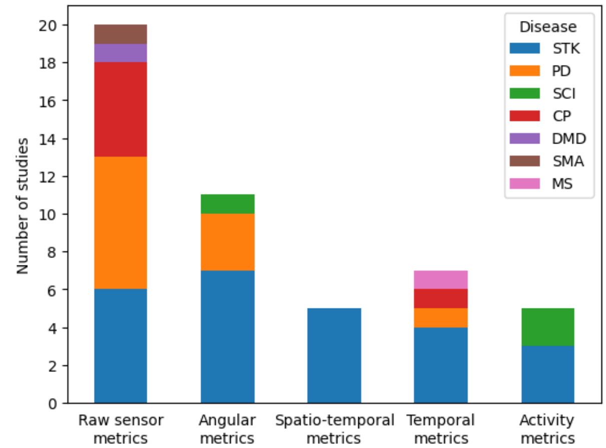

Fig. 8. Bar plot to describe the biomechanical metrics used according to the disease. Vertical axis represents the number of papers analyzed.

VI. Conclusion

In this study, we conducted a comprehensive review of IMU-based wearable systems designed for monitoring upper limb kinematics in individuals with neurological and neuromuscular diseases. Our evaluation encompassed both technical and clinical perspectives. From the analysis of the IMU-based systems examined, we derived the following key advantages and disadvantages:

Advantages:

- Compact dimensions and lightweight design, minimizing physical burden on users (dimensions <35 mm x 60 mm x 15 mm; weight<36 gr) [29], [35], [40], [50], [54], [56], [57], [84].
- Cost-effectiveness [41], [50], [56], [57], [84].
- User-friendly interface for both patients and clinicians [26], [56], [57], [84].
- Ability to directly obtain raw metrics from the system, even with a single sensor [27]–[30], [33]–[35], [40], [48], [49], [55], [56], [58]–[60], [76], [78], [84].
- Potential for comprehensive analysis of upper limb kinematics through kinematic modeling [32], [41], [43], [44], [54], [61]–[63].
- High accuracy of the system [32], [35], [41], [44], [50], [59], [60] .
- Non-intrusive system design that does not impede patient movements [27], [30], [33], [35], [40], [48], [50], [51], [56].
- Suitable for extended recording periods due to battery autonomy [31], [33], [45], [76].
- Capability for use outside equipped laboratory settings for motion analysis [27]–[31], [34], [35], [40], [45], [48]–[50], [76], [84].

Disadvantages:

- Systems incorporating IMUs or wires that may hinder patient movements [32], [44], [45], [54], [57], [59]–[61], [76].
- Challenges in performing sensor-to-segment calibration in subjects with motor diseases [35], [44], [62], [63].
- Insufficiency of IMUs for certain applications, leading to limited information [31], [33], [35].
- Inaccuracy due to absence or presence of a magnetometer [32], [50].

While the integration of IMU-based systems into clinical practice presents significant promise, challenges persist, including technical issues such as drift and magnetic interference, as well as the absence of standardized protocols. Despite these obstacles, considerable progress has been achieved over the last two decades. We conclude this review paper by sum-

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marizing the primary findings related to each of the proposed research questions.

A. What clinical protocols are used to evaluate upper limb kinematics in people with motor disorder using IMU-based systems?

Identifying standards for clinical practice to assess the upper limb kinematics using IMU-based systems in individuals with motor diseases is challenging. One of the major challenges from the clinical point of view is the implementation of the sensor-to-segment calibration in case of subjects with motor impairment. This practice is crucial for the accuracy of the data, but it is challenging to perform for a person with a motor disease. Even if the majority of the authors do not clearly explain the calibration process, it is possible to say that the most feasible calibration method is the static pose. In fact, the functional alignment would require the presence of a clinician to assist the patient in performing the functional movements.

Another critical aspect concerning the use of IMU-based systems in clinical practice is the choice of the number of sensors. They should not restrict the patients' movements while provide enough kinematic information to evaluate the motor status of the subject. The most used configuration consisted in using a sensor setup of four IMUs. This tendency may be attributed to the non-obstructive characteristic of a four-IMU system, which provides comprehensive kinematic information for one or more joints.

Regarding the placement of the IMUs, the majority of the studies place one IMU on the forearm segment at the wrist level. This placement allows capturing movement quality aspects such as speed and smoothness of the trajectory, even with just one sensor, which have been shown to be important indicators of motor function [48].

Despite these issues, there seems to be a tendency to use wearable IMU-based systems in the clinical practice, as they are easy to implement and provide useful information about the upper limb kinematics. Moreover, above all, the kinematic analysis performed with IMU-based systems allows to record the data in domestic and outdoor environments, thus collecting information about the real daily life use of the upper limb. This approach avoids the daily fluctuations of the patient (i.e., fatigue level, timing of the clinical assessment) and other limitations of standard clinical evaluation.

B. What are the technical characteristics and configurations of inertial sensors that are most suitable for clinical application?

Even if the IMU technology has gained popularity in the motion analysis field, its use in the clinical practice is still limited. Indeed, the majority of the studies included in this review have been conducted in a controlled environment. One of the challenges in a clinic setting or in a less controlled environment is the presence of ferromagnetic materials that can cause interference with the magnetometer. Hence, one option is to select IMUs without a magnetometer or exclude magnetometer data and analyze the information derived from the accelerometer and gyroscope. In fact, considering the latest advances in sensor fusion algorithms, it is not possible to definitively classify the magnetometer as a problematic concern. Indeed, it is important to note that only one study has addressed issues related to ferromagnetic interference, based on the data within this review.

Another choice the researcher has to make is whether to use IMU sensors with or without cables. The former option offers higher memory storage and battery life, making them well-suited for long-term recordings. Unfortunately, the complicated setup with cables might be too obtrusive and limit patients' movements. On the other hand, wireless IMUs offer limited-time captures but provide more ergonomic sensors that are better suited for uncontrolled environments, thus facilitating the recording of real daily-life movements. Hence, the solution would be choosing and developing the system according to the aim of study and the environment where the analysis will take place.

Regarding the usability, the type of fixation used to attach the sensor to the body segment represents a challenge, in particular for long-recording in an uncontrolled environment. It is necessary both limit the soft-tissue artefacts, to obtain reliable data, to ensure the comfort of the user, and to capture the real movement of the patient. For the sensor on the forearm, a common solution is to employ a watch-like band, which is both easy to wear and ensures a good fixation on the body. For the other segments, the most-widely used solution has been Velcro straps, a comfortable material that can be adapted to all types of body segments.

To check the accuracy of the data, it is common to compare the results with another motion analysis system. Generally, the IMU-based system is compared with a marker-based optical motion capture system, which is considered the gold standard. This review concluded that the data accuracy of IMU-based systems was sufficient to track the kinematics of the upper limb in patients with motor diseases, provided an accurate sensor-to-segment calibration had been performed.

To conclude, inertial tracking systems represent a feasible solution to monitor the upper limb kinematics in people with a motor disease in the clinical practice.

C. What biomechanical metrics obtained from IMU-based systems are useful for clinical practice?

IMU-based systems can be used to obtain features directly from accelerometer and gyroscope measurements (i.e., raw sensor metrics), or features based on a biomechanical model (e.g., angular or spatio-temporal metrics). The former are easily obtained from few sensors (even when using a single one), but usually lack an intuitive clinical interpretation. However, the simplicity to generate many motion features from these metrics makes them good candidates for real-time and machine learning applications. On the contrary, features based on a biomechanical model align more closely with clinical applications, but require an IMU-based system with at least two sensors in consecutive segments to obtain at least a single-joint kinematics.

Nevertheless, raw sensor metrics, angular metrics and spatio-temporal metrics have all shown to be useful for the evaluation of the kinematics of the upper limb in people with motor diseases. As a matter of fact, several of the reviewed studies successfully used these types of metrics to correctly distinguish between healthy subjects and people with motor diseases, therefore being able to identify the distinctive motor characteristics of the disease and assess the level of motor function of the analyzed patients. In some cases, these metrics were even able to provide additional information related to the participant's movements (e.g., compensatory movements), which are otherwise not perceptible through the simple observation of a clinician. For this reason, these metrics enhance the comprehensive evaluation of the patients. This might prove the effectiveness of the IMU-based system in quantitatively and objectively assessing the motor status of people with motor diseases.

Temporal metrics, such as the time needed to complete a task, can be a good indicator of a patient's motor function since longer duration of a task can be associated with poor motor control. The use of the sensors can also help analyzing the time needed for each sub-phase of a movement, enhancing the comprehension of motor control during each phase.

Recording data outside of the laboratory for a long period of time allows us to measure new parameters, such as activity metrics. Those metrics could be more representative of the patient's daily-life activity and could help the clinicians to better tailor the treatment and monitor the progression of the disease.

In conclusion, in the future, the data collected with IMU-based systems might represent a valid alternative to subjective clinical evaluations, as they provide a quantitative assessment of the patients' motor status. They will also allow to continuously monitor the patient during the whole day to obtain more representative information of the motor disease in real life.

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TABLE I

TABLE SUMMARIZING THE CLINICAL ASPECTS OF THE REVIEWED ARTICLES. THE TABLE DESCRIBED THE AIM OF THE WORK, THE CLINICAL INFORMATION OF THE PATIENTS (AGE AND DISEASE) THE MOVEMENTS THE AUTHORS ASKED THE PATIENTS TO PERFORM AND THE PLACEMENT OF THE IMU. MOVEMENT TASKS: MFM: MOTOR FUNCTION MEASURE; NINE PEG HOLE: NPH; FUGL-MEYER ASSESSMENT:FMA; ACTIVITY OF DAILY LIVING: ADL; UNIFIED PARKINSON'S DISEASE RATING SCALE: UPDRS; FINGER TO NOSE: FTN; MINNESOTA TEST: MT; BOX AND BLOCK TEST: BBT;

Authors	Aim of the study Type of the study	Patient Clinical Information	Clinical Scale Movement Task	IMU Placement
[28]	Quantitatively characterize the motor disease(ES)	Children (m=81) with SMA	MFM	1 IMU - forearm at wrist level
[44]	Quantitative assessment of upper limb kinematics of Stroke survivors (PS)	Adult stroke survivors (m=1)	NPH	4 IMUs - hand, forearm, upper arm torso (shoulder level)
[63]	Quantitative assessment of upper limb kinematics in stroke survivors (PS)	Adults Stroke survivors (m=10)	FMA	8 IMUs - hand, forearm, upper arm, torso (at shoulder level and chest)
[69]	Recognize movement of the forearm using pattern recognition with a single IMU in stroke patients (OB)	Adults Stroke survivors (m=4)	ADL	1 IMU - on the forearm at wrist level
[50]	Assessment of shoulder motion in patient with Cervical Spinal Cord Injury (EV)	Adults with SCI (m=8)	NP	2 IMUs- the forearm, at wrist level, and on the upper arm
[29]	Assessment of activity metrics in patient with Cervical Spinal Cord Injury (OB)	Adults with SCI (m=12)	ADL	2 IMUs- on the forearm, at wrist level, and on the torso
[30]	Assessment of activity metrics in patient with Cervical Spinal Cord Injury (OB)	Adults with SCI (m=30)	NP	1 IMU - on forearm, at wrist level
[56]	Motor assessment of patient with Parkinson Disease to distinguish between healthy subject and patients (OB)	Adults with Parkinson Disease (m=30)	UPDRS	4 IMU - on hand and forearm, at wrist level
[40]	Development of an IMU-based system as auxiliary diagnostic system for Parkinson's Disease (OB)	Adults with Parkinson Disease (m= 50)	UPDRS	1 IMU - on the forearm, at wrist level
[31]	Quantitative assessment in stroke survivors in a controlled and uncontrolled environment (PS)	Adults Stroke survivors (m=5)	NP	1 IMU - on the forearm, at wrist level
[53]	Characterization of upper limb movement in patient with Parkinson's Disease to provide a new index to assess bradykinesia (PS)	Adults with Parkinson Disease (m=13)	NP	4 IMUs - on hand, forearm, at wrist level, upper arm and torso (shoulder level)
[58]	Quantitative analysis of bradykinesia and rigidity in patient with Parkinson's Disease (OB)	Adults with Parkinson Disease (m=14)	UPDRS	5 IMUs - on hand, forearm (wrist level), upper arm
[84]	Analysis and comparison of upper limb movement in patients with multiple sclerosis and healthy subjects (OB)	Adults with Multiple Sclerosis (m=60)	FTN	1 IMU - on the forearm (wrist level)
[32]	Assessment of the upper limb in stroke patients during a standard clinical assessment and daily-life (OB)	Adults Stroke survivors (m=8)	FMA	4 IMUs - forearm (wrist level), upper arm and torso (shoulder and sternum level)
[45]	Collection kinematic data and classify the movement of children with Cerebral palsy to determine the effectiveness of the therapy (ES)	Children with Cerebral Palsy (m=140)	NP	2 IMUs - on the hand and forearm, at wrist level
[49]	Quantitative assessment of cerebellar ataxia to predict the presence and severity of the disease (OB)	Adults with Cerebral Palsy (m=39)	NP	Configuration 1: 1 IMU hand (dorsal side) Configuration 2: 1 IMU-forearm(wrist level)
[76]	Quantify the range of upper limb movements using IMU (PS)	Children and adults with DMD (m=7)	MT, BBT, ADL	1 IMU on the forearm, at wrist level
[27]	Development of a IMU-based system to promote movement during the day of the affected arm in stroke survivors (OB)	Adults Stroke survivors (m=20)	NP	1 IMU on the forearm, at wrist level
[33]	Measurement of upper limb function in children with hemiparesis (OB)	Adults Stroke survivors (m=10)	BBT	1 IMU on the forearm, at wrist level
[35]	Estimation of movement impairment	Children Stroke survivors Children with Cerebral Palsy (m=30)	Random voluntary movements	2 IMUs- on the forearm, at wrist level, and torso
[51]	Quantitative evaluation of upper limb motor function in stroke survivors (OB)	Adults Stroke survivors (m=23)	Random voluntary movements	2 IMUs- on the forearm, at wrist level, and torso
[43]	Quantitative evaluation of upper limb motor function in stroke survivors during clinical assessment (OB)	Adults Stroke survivors (m=34)	NP	2 IMUs- on forearm, at wrist level, and torso, at sternum level
[54]	Assessment of motor impairment in Parkinson's Disease patiens (OB)	Adults Stroke survivors (m=28)	ARAT	4 IMUs- hand, forearm (wrist level), upper arm and torso (sternum level)
[59]	Assessment of therapy effectiveness for Parkinson's disease patient (ES)	Adults with Parkinson Disease (m=60)	UPDRS	5 IMUs- hand, forearm (wrist level), upper arm, torso (back and waist level)
[60]	Quantitative assessment of motor function in Parkinson's disease patient to support clinicians in objectifying PD diagnosis (OB)	Adults with Parkinson Disease (m=36)	UPDRS	5 IMUs- hand, forearm (wrist level), upper arm, torso (back and waist level)
[57]	Assessment of upper limb movement impairment to improve the understanding of the disease and assess the effectiveness of the interventions (PS)	Adults with Parkinson Disease (m=40)	UPDRS	4 IMUs- forearm (wrist level) hand (thumb, index and middle finger)
[62]	Investigate the inter joint coordination of the upper limb in stroke survivors across different movement tasks (OB)	Adults Stroke survivors (m=10)	FMA	8 IMUs- hand, forearm, upper arm, and torso (shoulder level)
[41]	Develop an automatic segmentation and recognition methodology to identify motor pattern during activities of daily living in Parkinson disease patients (OB)	Adults Stroke survivors (m=26)	FMA, ADL	5 IMUs- hand, forearm, upper arm, and torso (shoulder and sternum level)
[55]	Evaluate metrics to describe daily-life arm movement performance in stroke subjects in a simulated daily-life setting (OB)	Adults with Parkinson Disease (m=13)	NP	4 IMUs- hand, forearm (proximal and distal part) and upper arm
[61]	Quantitative assessment of trunk movement in children with Cerebral Palsy (OB)	Adults Stroke survivors (m=17)	ADL	6 IMUs- hand, forearm ,upper arm, torso (sternum, shoulder and waist level).
[78]	Quantitative assessment of trunk movement in children with cerebral palsy (OB)	Children and Adults with Cerebral Palsy (m=20)	ADL	1 IMU- torso (sternum level)
[34]	Quantitative assessment of upper limb movement in individuals with cerebral palsy (OB)	Children and Adults with Cerebral Palsy (m=18)	ADL	3 IMUs- on the hand, forearm and upper arm
[48]	Estimation of clinical score of upper limb movement in stroke survivors (ES)	Adults Stroke survivors (m=21)	ARAT	1 IMU on the forearm- at wrist level
[26]	Investigate the feasibility of self-directed home training with an platform based on IMU (ES)	Adults Stroke survivors (m=11)	FMA	3 IMUs- on the forearm, at wrist level, on the upper arm and on the torso (at sternum level).

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TABLE II

Table of the technical aspects of the IMU-based system and the biomechanical metrics obtained. The brand and the company of the IMU was reported in the table, when this data was declared in the articles. When a self-built custom device is used, the sensor chips used are indicated in brackets. Abbreviations: w/M (magnetometer used); w/oM (magnetometer absent or not used); Fs (Recording Sampling Frequency); BPF/LPF/HFP (Band / Low / High-pass filter); KF/CF/MAD (Kalman / Complementary / Madgwick filters); RSM/ANM/STM/TEM/ACM (RawSensor / Angular / Spatio-temporal / Temporal / Activity Metrics); TD/FD (Time / Frequency domain)

Article	IMU	Data Collection and Pre-processing	Biomechanical Metrics	General Remarks
[28]	Actymio (Sysnav, Vernon, FR) w/M.	N/A	RSM(TD)	Changes in the motor assessment detected over 6 months in children with SMA, in real-life settings
[44]	MTx (Movella, Enschede, NL) w/M.	Fs = 120 Hz, Xsens KF	STM	Provides additional information on the clinical recovery of stroke survivors while performing the NHPT
[63]	Custom [ST-LSM330DLC] w/o M.	Fs = 200/100 Hz (gyr/acc), CF(MAD), ZUPT	ANM	The IMU-based system shows high potential to objectively assess motor function of the upper extremity of stroke patients
[69]	Shimmer-9DoF (Shimmer, Dublin, IE) w/o M.	Fs = 50 Hz, BPF (0.1-12 Hz)	RSM(TD)	The detection of typical arm movement can provide an indication of rehabilitation progress of stroke survivors
[50]	MetaMotionR (MBientLab, San Francisco, US) w/o M.	CF(MAD)	ANM	Used as tool to objectively monitor the shoulder movement of patients with cervical spinal cord injury
[29]	Custom “Resense” w/o M [ADXL-345, TDK-ITG3200]	Fs = 50Hz	ACM	Activity metrics be me clinically relevant to gain insights in the long-term evolution of patients in the home environment
[30]	Custom “Resense” w/o M [ADXL-345, TDK-ITG3200]	Fs = 50Hz	ACM	Data collected in home environment can be used to track clinical outcomes during rehabilitation in patients with SCI
[56]	Custom “SensHand V1” w/M [L3G4200D, LSM303DLHC]	Fs = 100 Hz, LPF (5Hz) for repetitive exercises, BPF (0.5-15/20Hz) for tremor, ZUPT	RSM(TD,FD)	Data collected in home environment can be used to track clinical outcomes during rehabilitation in patients with SCI
[40]	BWT901CL (Witmotion, Shenzen, CN) w/o M.	Fs = 50 Hz, LPF (20Hz), KF	RSM(TD,FD)	Task with hand movement has satisfactory classification for Parkinson’s Disease patients
[31]	Custom IMU w/o M [MPU9250]	CF(MAD), Median Filter	ACM	The IMU-based system is a feasible method to measure relative arm use in hemiparetic patients at home
[53]	IGS-180 (AIQSynertial, Brighton, GB) w/M.	N/A	ANM	The bradykinesia index is a tool to assess objectively and quantitatively the bradykinesia in Parkinson’s Disease patients
[58]	OPAL (APDM, Portland, US) w/M.	HPF (1Hz), BPF (4-8 Hz) for tremor, BPF (1-4Hz) for bradykinesia	RSM(TD,FD), TEM	Analyzing the data from an IMU-bases system is possible to obtain a quantitative analysis of bradykinesia and rigidity in patients with Parkinson’s Disease
[84]	3-Space™ Wireless 2.4GHz (YostLabs, Ohio, US) w/M.	Fs = 200 Hz, KF, LPF (5Hz) for gyroscope data	TEM	Quantitative analysis of bradykinesia and rigidity in patients with Parkinson’s Disease
[32]	Xsens full-body suit (Movella, Enschede, NL) w/M.	Fs = 20 Hz, Xsens KF	ANM, STM, ACM	Activity metrics derived from continuous measurement are more sensitive to changes compare with clinical assessments
[45]	Custom IMU w/M [MPU9250]	CF, Savitzky–Golay filter	RSM(FD)	Data from IMU-based system can be used to classify CP movement
[49]	Custom “BioKinTM” w/o M [MPU9250]	Fs = 50 Hz, CF	RSM(TD,FD)	Data from IMU-based system can be used to classify CP movement
[76]	Actymio (Sysnav, Vernon, FR) w/M.	KF	RSM(TD)	The variables, obtained from the IMU-based device, well represent the movements performed by DMD children
[27]	Shimmer 6-axis IMU (Shimmer, Dublin, IE) w/o M.	Fs = 256 Hz, LPF (10Hz)	RSM(TD)	Wearable sensor data can provide clinically-meaningful indicators of the motor impairments in stroke survivors
[33]	Custom “Resense” w/o M [ADXL-345, TDK-ITG3200]	CF(MAD), HPF (0.3 Hz)	ACM	Variables linked to arm function of stroke survivors can be monitored during daily life with and IMU-based device
[35]	Physilog4 (GaitUp, Lausanne, CH) w/o M.	N/A	RSM(TD,FD), TEM	Assessment of the upper limb movement with parameters not easily quantified by standard clinical observation
[51]	MTw Awinda (Movella, Enschede, NL) w/M.	Fs = 100 Hz, Xsens KF, LPF (8 Hz) for acceleration	RSM(TD)	IMU-based system can help estimating the impairment of stroke survivors performing minimally-burdensome task
[43]	Custom IMU w/M [MPU9150]	Fs = 50 Hz, Hierarchical information particle filter	ANM, STM, TEM	Can help in evaluating the motor status of stroke patient and supporting the rehabilitation process
[54]	Reference N/A, w/M.	KF	RSM(TD), ANM, STM	Quantification with IMU-based system during ARAT assessment can provide better insight into arm motor function
[59]	Movit G1 (Captiks, Rome, IT) w/o M.	Fs = 50 Hz, LPF (10 Hz)	RSM(TD,FD), ANM	Wearable device can be a valid support to assess a correct evaluation of PD in its early stage
[60]	Movit G1 (Captiks, Rome, IT) w/o M.	Fs = 50 Hz	RSM(TD,FD), ANM	Can provide an objective way to monitor patients’ response and to personalize the therapy based on measurable outcomes
[57]	Custom “SensHand” w/M [L3G4200D,LSM303DLHC]	Fs = 100 Hz, LPF (5Hz), BPF(0.5-15/20Hz) for tremor analysis, ZUPT	RSM(TD,FD)	IMU-bases system can distinguish between healthy subject and Parkinson Disease patient
[62]	Custom IMU w/o M [ST-LSM330DLC]	Fs = 100/200 Hz (acc/gyr), CF(MAD), LFP (10Hz), ZUPT	ANM, TEM	Can provide additional information regarding the functional status of stroke patients
[41]	MVN Awinda (Movella, Enschede, NL) w/M.	Fs = 60 Hz, Xsens KF	STM, ANM	Shows the importance to assessing different movement tasks of the real world to get a more complete picture of post-stroke patients
[55]	Technaid (Technaid, Madrid, ES); magnetometer info N/A	Fs = 100 Hz	RSM(TD)	Automatic labelling of continuous upper limb activity. Tool to interpret tremor in PD patients and monitor treatment
[61]	MVN Biomech (Movella, Enschede, NL) w/M.	Fs = 120 Hz	STM	Metrics of hand movements can be used to objectively assess performance of arm movement in stroke patients
[78]	MTw (Movella, Enschede, NL) w/M.	Xsens KF, LPF (5Hz)	RSM(TD)	First step to better individualize evaluation and treatment for trunk control in Dyskinetic CP children
[34]	MTw Awinda (Movella, Enschede, NL) w/M.	N/A	RSM(TD)	The pathological movements of individuals with Dyskinetic CP can be captured with IMU-based system.
[48]	ZurichMove (ZurichMove, Zurich, CH) w/o M.	Fs = 50 Hz, Analytical solution of sensor fusion	RSM(TD,FD)	It is feasible to obtain accurate estimates of the ARAT score with an IMU-based system
[26]	MotionPod3 (Movea, Grenoble, FR) w/M.	CF(MAD)	ANM	Home therapy, with an IMU-based system, is safe and can provide rehabilitative training in a high dose