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Quantitative Upper Limb Impairment Assessment for Stroke Rehabilitation: A Review

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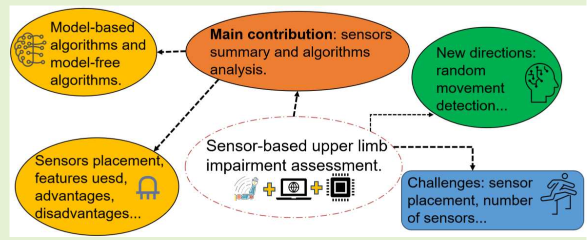
***Abstract*—With the number of people surviving a stroke soaring, automated upper limb impairment assessment has been extensively investigated in the past decades since it lays the foundation for personalised precision rehabilitation. The recent advancement of sensor systems, such as high-precision and real-time data transmission, have made it possible to quantify the kinematic and physiological parameters of stroke patients. In this paper, we review the development of sensor-based upper limb quantitative impairment assessment, concentrating on the capable of comprehensively and accurately detecting motion parameters and measuring physiological indicators to achieve the objective and rapid quantification of the stroke severity. The paper discusses various features used by different sensors, detectable actions, their utilization techniques, and effects of sensor placement on system accuracy and stability. In addition, both the advantages and disadvantages of the model-based and model-free algorithms are also reviewed. Furthermore, challenges encompassing comprehensive assessment of medical scales, neurological deficits assessment, random movement detection, the effect of the sensor placement, and the effect of the number of sensors are also discussed.**



***Index Terms*—Wearable sensors; Stroke assessment; Machine learning; Deep learning; Upper limb impairment**

I. Introduction

STROKE has tremendous impacts on the global public health and the number of stroke survivors is still increasing significantly [1]–[3]. According to the World Stroke Organization annual report in 2022, there is an annual increase of around 12.2 million stroke cases globally [4]. Besides, among stroke patients, over two-thirds experience the upper limb impairment [5], generally resulting from five main aspects, including paralysis [6], abnormal motor coordination [7], dystonia [8], sensory impairment [9], and the ability to individuate the fingers [10], [11]. These five aspects may coexist in various combinations and collectively interfere with the movement function [12] consequently reducing the motion ability of stroke survivors to perform activities in the daily life independently. Moreover, the continuously growing number of stroke patients has imposed a substantial economic burden on the society. It was estimated that, in 2022, the losses caused by the stroke are equivalent to 1.12% of the global gross domestic product (GDP) for that year [13]. This impact is particularly severe for low-income and middle-income countries. To mitigate impacts of the upper limb impairment and reduce the losses caused by stroke, post-stroke rehabilitation therapies have been introduced.

Stroke rehabilitation is a highly effective way for restoring the motion function of stroke patients [14]. Previous studies have shown that the severity of the upper limb impairment can be reduced after the rehabilitation training and considerable motion function can be recovered [15], [16]. However, it is difficult to choose an appropriate rehabilitation training strategy for a patient among the numerous strategies, because patients may respond positively to some of the rehabilitation strategies, but not others [17], [18]. In addition, as the severity of the disability changes, the required rehabilitation strategy should also be constantly adjusted [19]. Therefore, quantitative upper limb impairment assessment is imperative to enable the selection of optimal rehabilitation strategies based on the condition of a patient.

Traditional upper limb quantitative impairment assessment method evaluates the motion function using clinical medical scales, such as Fugl-Meyer (FMA) [20], Wolf Motor Function Test (WMFT) [21], National Institutes of Health Stroke Scale (NIHSS) [22], and Action Research Arm Test (ARAT) [23],

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TABLE I
COMPARISON OF TRADITIONAL MEDICAL SCALES AND AUTOMATIC ASSESSMENT TECHNOLOGY

Assessment methods	Clinical medical scales			Automatic assessment
	FMA	WMFT	ARAT	
Duration	20-30 min	About 30 min	About 10 min	Cost less than scales
Applications	Clinical use	Clinical use	Clinical use	Clinical and home use
Operation	Therapist and 14 tools	Therapist and 12 tools	Therapist and 11 tools	1 or more sensors
Scoring Rules	Visual estimation	Visual estimation	Visual estimation	From sensor data

Fig. 1. Number of publications referring to sensor-based post stroke rehabilitation assessment indexed by the Web of Science, IEEE Xplore, and Scopus, and indicates continuously increasing of the research in this field.

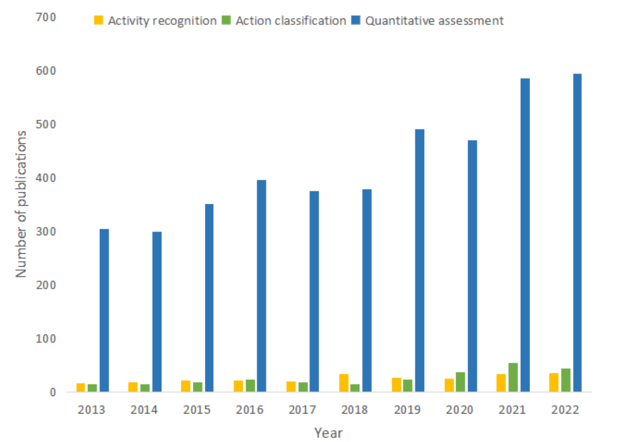


Fig. 2. Distribution of papers published in the three categories of the impairment assessment system.

etc. Therapists utilize these scales to assess the motion function of the patients by scoring the motion based on the tasks on the scales. However, these scales usually consume a lot of time and require therapists and patients to assess the score one by one. Therefore, the demand for the automated impairment assessment has gradually increased due to the strengths of the dependability, accuracy, speed and convenience, as shown in Table I [24]. Compared with traditional methods of visually assessing the motion function [12], automated impairment assessment method assesses the motion function of patients by collecting their motion data through the use of wearable sensors or a combination of other sensors [25]. According to the application of sensors, the accuracy of the impairment assessment system is greatly improved because it could detect slight changes in the motion through quantified data changes [26]. Moreover, the reliability of the impairment assessment system has also been significantly enhanced in comparison to visual estimation by the therapist [27]. Due to the advantages of sensing technology, various systems have been developed that are capable of achieving continuous, accurate, and automated assessment of the upper limb function.

Sensor-based upper limb impairment assessment, a crucial component of the stroke rehabilitation process, has gained significant attentions and research motivations in recent years, as illustrated by the rapid growth of the number of assessment-related publications in Fig. 1. Specifically, post-stroke impairment assessment systems could be classified into three typical categories: activity recognition, action classification, and quantitative impairment assessment to evaluate the condition of patients [28]. Fig. 2 demonstrates a significant increase in employing assessment methods for stroke impairment assessments in past 10 years. It is obvious that the quantitative impairment assessment has attracted more research interests in the past few years due to its visibility, quantification, and comparability. Therefore, this review focuses on the current sensor-based methods for quantitative upper limb impairment assessment.

A. Limitations in Previous Reviews

Several reviews have analyzed various components of upper limb impairment assessment systems for stroke rehabilitation. Firstly, multiple reviews have focused on the introduction of different medical scales. For example, Lang et al. [29] reviewed all these scales used for the upper limb impairment assessment and analyzed how these scales should be selected. Medica [30] reviewed medical scales that only assessed the trunk. However, these reviews only focused on the medical scales, and did not fully demonstrate their impacts. Secondly, previous reviews have provided summaries of the sensor features utilized and their corresponding computational methods [31]–[35]. However, their focuses are limited to the specific category of sensors, such as inertial measurement unit (IMU) [31], [32], surface electromyography (sEMG) sensors and electroencephalography (EEG) sensors [33], or accelerometers [34], [35]. It is insufficient to solely review the application of a particular category of sensors, as actual research may employ numerous categories and varying quantities of sensors. Although Boukhennoufa et al. [28] reviewed multiple categories of sensors, they only discussed the differences in sensors placement. In addition, previous reviews summarized machine learning algorithms used in impairment assessment systems. One study highlighted the advantages of four machine learning algorithms and the number of studies on each [28], while Duque et al. detailed data processing and feature engineering methods [36]. In summary, there is currently no comprehensive review that not only presents and analyzes commonly used sensor types, but also summarizes the application of machine learning, deep learning, and kinematic indicators based algorithms in upper limb impairment assessment systems.

B. Main Contribution of This Review

Different to previous surveys, this review aims to provide a comprehensive and in-depth overview of the automated upper limb impairment assessment systems. By comparing the utilization techniques, placement, selected features, detectable actions, advantages and disadvantages of the sensors commonly used in the systems, it could possibly provide some help for future researchers in this field. A summary of the application scope of various quantification algorithms (model-based and model-free algorithms) could also potentially help researchers choose appropriate quantification methods. In addition, the challenges and opportunities including comprehensive assessment of medical scales, neurological deficits assessment, random movement detection, the effect of sensor placement and number of sensors would offer valuable insights for further research in this field.

This paper is organized according to the following structure. Section II analyzes which kinematic indicators or physiological indicators could be detected by the different classes of sensors used in the current studies, and the advantages of each class of sensors. Then the performance of different quantification algorithms and the algorithm optimization methods are summarized in Section III. Subsequently, Section IV describes the challenges and opportunities of developing an upper limb impairment assessment system. Finally, a conclusion is given in Sections V.

II. Sensors with Kinematic and Physiological Indexes

The design of a standard upper limb quantitative impairment assessment system generally includes the selection of sensors and quantitative algorithms. The selection of sensors is to select the type of sensors for detecting the kinematic and physiological parameters intended to be measured by the system. Various types of sensors have been used in the upper limb impairment assessment systems in previous studies. This review summarizes them into four categories according to their functions and measurement principles: motion sensors, force sensors, bio-electrical signal sensors, and visual sensors. In this section, the utilization of these sensors is presented, including their deployments, kinematic or physiological indicators and multi-modal fusion. The extracted features, recognized motions, sensor deployments, as well as the advantages and limitations of each sensor, are shown in Table II, and Fig. 3 presents the deployments of sensors described in Table II.

A. Motion Sensors

Motion sensors can be used to detect the motion of an object, generally including accelerometers [38]–[40] and IMUs [41], [42]. They are used in most of the upper limb impairment assessment studies to measure kinematic indexes related to the object position, velocity, acceleration, rotation angle, and attitude, etc. [38], [39], [41]–[44]. Specifically, they can be directly or indirectly connected to the measured parts of the human body. For example, the motion sensors could be installed by using adhesive tape and straps [45], [46], or embedded in a watch worn by the object [47]. In this manner, they could collect the motion information of the object in real-time and transmit the data to the processor.

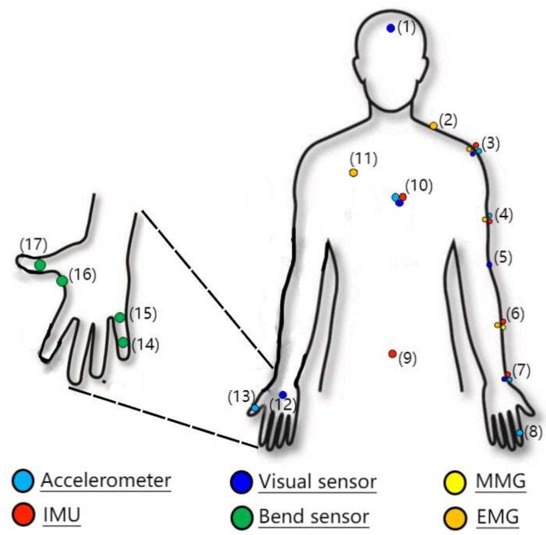


Fig. 3. Placement of different sensors: (1) forehead, (2) trapezius, (3) shoulder, anterior deltoid, medial deltoid, (4) arm, triceps brachia, biceps brachia, (5) elbow, (6) brachioradialis, (7) wrist, (8) index finger, (9) waist, (10) sternum, (11) pectoralis major, (12) hand, (13) thumb, (14) proximal interphalangeal (PIP) joint, (15) metacarpophalangeal (MCP) joint, (16) abduction angle of the MCP joints, and (17) interphalangeal (IP) joint [37]

Accelerometer as shown in Fig. 4(a) is one of the most widely used motion sensors with the advantages of small size, low energy consumption, high measurement accuracy, and good stability [46], [48]. In the upper limb impairment assessment studies, accelerometers are placed on the upper limbs of stroke patients to collect the acceleration data along three axes. The collected data could help evaluate the motion function during various upper limb activities [49]. Through the calculation and deformation of the acceleration data, the kinematic parameters related to the movement time, distance, and speed could be further obtained, such as deceleration time, movement distance, average velocity, and peaks, etc. [50]–[52]. Due to the advantages in size, cost, consumption, and ability to capture more kinematic parameters, accelerometers have been widely implemented to establish the simpler upper limb impairment assessment system for stroke patients. However, to comprehensively analyze the upper limb motion function, more kinematic parameters collected by multiple types of sensors are also necessary.

IMU combines an accelerometer, a gyroscope, and a magnetometer, which can additionally collect kinematic information related to the rotational speed and direction of the wearer

(a) (b)

Fig. 4. Motion sensors: (a) Accelerometer-based wrist-worn activities monitoring system [53]. (b) IMU-based upper body motion capture system, LPMOCAP [54].

(a) (b) (c)

Fig. 5. Force sensors: (a) Pressure sensor [57]. (b) A flex sensor-based hand flexion and extension monitoring glove [58]. (c) A strain sensor-based sensing shirt [61].

comparing with only using accelerometers. Fig. 4(b) displays the utilization of IMUs. Moreover, Rana et al. [55] found that after packaging these three types of sensors into an IMU, it could be better applied to the upper limb impairment assessment system due to the reduction in volume and energy consumption. Although the performance of these three sensors may be degraded due to the cumulative drift and errors, the data collected by IMU is still stable through utilizing data fusion techniques [56]. Therefore, IMU is becoming one of the commonly used primary sensing devices, it not only meets the needs for kinematic information collection but also is with small size, excellent stability, and minimal impacts on the normal activities of the wearer.

B. Force Sensors

Force sensors, mainly including pressure sensors, flex sensors (also known as bend sensors), and strain sensors, are usually for the measurement of force or pressure indexes exerted by the hand or upper limb muscles. Analysis of the data collected from these force sensors can be used to quantitatively assess the muscle strength and motion control of patients.

Pressure sensor as shown in Fig. 5(a) is mainly used for action segmentation in relatively complex motions and situations involving contact with other objects, which could help classify complex motions in detail, improving the accuracy of the system. Lee et al. [37] installed a pressure sensor on an object grasped by the stroke patient during stretching. They used the change time to segment the overall motion collected from IMU. Furthermore, pressure sensors have been employed to gather grip strength data from stroke patients, broadening the capability of the system to detect various motions, such as those associated with grip strength on the FMA scale [57]. However, pressure information cannot reflect the functional information of the upper limbs well, thus pressure sensors are usually used in combination with other sensors.

The next important force sensor is the flex sensor, which can be used to measure the flexion and extension of individual fingers in an upper limb impairment assessment system. Previous studies involved assembling multiple flex sensors on a glove as shown in Fig. 5(b), and attaching them to all joints of each finger [58]. When these sensors detect the finger flexion or extension, the flexible resistance value within them changes accordingly, generating corresponding electrical signals. Analyzing these signal changes allows for a quantitative evaluation of the finger flexion, extension ability, and flexibility [57], [59]. Moreover, flex sensor can also be installed between fingers to obtain the joint abduction ability of the hand [60], making the flex sensor be an appropriate choice to collect hand-related kinematic parameters, such as hand movement time, angle, and velocity, etc.

With the development of the electronic textile technology, embedding sensors into fabric has become a reality, where strain sensors are integrated into the shirt to monitor arm motions [62] (shown in the Fig. 5(c)). The specific implementation principle is that the resistance value of the conductive elastomer printed on the clothes will change because the stretching force changes the shape of the clothes [61]. However, this method has a significant drawback as there is no direct correlation between the deformation of the conductors printed on each position of the clothes and the mechanical parameters of the human body. Additionally, it is susceptible to various influences, thus strain sensors have rarely been studied for upper limb impairment assessment systems due to these limitations [61].

C. Bio-electrical Signal Sensors

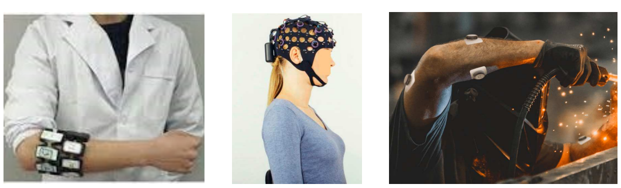
The following type of sensors that have been widely used in the upper limb impairment assessment systems for stroke patients is the bio-electrical signal sensors, including sEMG sensors (see Fig. 6(a)), EEG sensors (see Fig. 6(b)), and mechanomyography (MMG) sensors (see Fig. 6(c) [74]). They are used to measure and analyze the electrical or mechanical signals generated by the upper limb muscle activities. These signals are then processed and analyzed to extract relevant kinematic or physiological features, such as muscle activation patterns, brain wave patterns, and motion strategies. By analyzing these characteristics, the motor control ability and motor coordination ability of patients could be further estimated.

As one of the most used bio-electrical signal sensors, sEMG sensor could collect the bio-electrical activities of muscles to assess the muscle function and motor control. Yang et al. [72] placed an sEMG sensor on the forearm of the patient to collect muscle signals during different motions of the hand, and then they used a robotic arm to simulate the recognized hand motions. After that, a remote impairment assessment system

TABLE II
COMPARISON OF DIFFERENT KINDS OF SENSORS

Name	Placement	Motors	Features obtained	Advantage	Disadvantage
Accelerometer	1) Midpoint of the back of forearm [63]. 2) Sternum, arm, wrist, thumb, and index finger [19], [37], [64]. 3) Upper arm and shoulder (Front and back), back of the forearm [65].	Forearm to the table, extend the elbow, hand to the table, reach and retrieve, lift can, lift a pencil, flip cards, turn the key in a lock.	1) Frequency domain: energy, maximum signal amplitude, minimum signal amplitude, mean signal amplitude, variance, skewness, kurtosis, signal entropy, the frequency content of the signal, the ratio of the magnitude of the dominant frequency and total signal energy. 2) Time domain: minimum, maximum, mean value, root mean square value, spearman correlation coefficients, and duration.	1) User-friendly data collection, easy patient attachment. 2) Cost-effective for system construction. 3) Provides real-time feedback on patient performance.	1) Limited details on strength, fine motor, and finger independence. 2) Inaccurate detection of flexion, extension, and rotation movements. 3) Susceptible to interference from factors like noise and drift.
IMU	1) One wrist [47], [66]. 2) Torso, upper arm, lower arm, hand [67]. 3) Both hands, upper and lower arms, left and right shoulders, and torso [68]. 4) The waist, upper arm, forearm, and hand [69].	Donning/doffing shoes, grooming, stacking boxes, cutting playdough, folding towels, writing, sorting items into a tackle box, typing, buttoning a shirt, uncapping, and drinking.	1) Frequency domain: mean, median, maximum, spectral energy, spectral centroid, ratio of main frequency to total signal energy, mean power, frequency radio. 2) Time domain: maximum, minimum, average, median, amplitude, root mean square, spearman correlation coefficients, duration, speed (average, maximum, change, entropy), zero crossing, trunk forward angle, joint angle, trajectory accuracy, movement, shakiness, interquartile range, tenth and ninetieth percentiles, mean absolute value, standard deviation, variance.	1) Multiple sensors capture comprehensive 3D motion data. 2) User-friendly, compact, lightweight, easy to install in diverse environments. 3) Enables real-time monitoring with prompt feedback. 4) Collects detailed upper limb movement information from various positions.	1) Unable to capture subtle movements like facet joint angles or finger details. 2) Sensor drift causes motion data accumulation errors over time. 3) Unable to identify indicators related to upper limb strength.
Bend sensors	MCP joints and PIP joints of the four fingers, MCP and IP joints of the thumb, and abduction angles of the MCP joints between adjacent fingers. [58], [60].	Detect reach and grasp motors with a rectangular, a concave, or a convex object separately. Wrist flexion and extension, Lateral pinch, Finger touch.	Time to perform different actions, joint range of motion, timing of peak joint extension, within-shape joint angle variability across all the joints, amplitude of sensor data, mean value, root mean square, jerk, approximate entropy.	1) Highly flexible, covering various hand joints for capturing subtle changes. 2) User-friendly glove design reduces the need for repositioning before each use. 3) Cost-effective for system construction.	1) Limited details beyond flexion and extension. 2) Limited accuracy. 3) Easy to damage, require regular inspection and replacement.
Pressure sensor	Embedded on a cup [70].	Grip Strength During Grasping.	Summed force, time to max, duration, variance, time duration max aperture, average, standard deviation.	1) Quantification of grip strength and changes. 2) Flexible application.	1) May affect the movement of patients. 2) Limited information available.
Strain sensors	Contains 29 sensing segments distributed over the arm, forearm, and shoulder [61].	Arm adduction, forearm rotation, elbow flexion and extension, eating, combing.		1) User-friendly, no skin adherence. Without time and space restrictions. 2) Minimizes sensor impact on limb movement.	1) Poor stability. 2) Inaccurate due to variations in body shape and clothing position.
MMG	On the underside of the forearm [71].	14 FMA-UE tasks include 9 Gross Motor Tasks and 5 Hand/Wrist Motor Tasks.	1) Time domain: modified mean absolute value, log detector, average amplitude change, difference absolute standard deviation, root mean square, power, and trapezium integration. 2) Frequency domain: dominant frequency, mean frequency, median frequency, mean power, frequency radio, peak frequency radio, variance central frequency.	1) Low work environmental requirements. 2) Stable, with a robust signal less affected by changes in skin impedance.	1) High technical requirements require professional signal processing. 2) Limited detected information. 3) Less effective in patients with lower muscle activity levels.

EMG	Muscles in the front and back of the upper arm, muscles in the front and back of the shoulder, muscles in the back of the forearm. Pectoralis major, trapezius, anterior deltoid, medial deltoid, biceps brachii, triceps brachii, and brachioradialis. [65], [69], [72]	Gestures include agree, close/open hand, pointer, thumb and middle finger, thumb and little finger, flex/extend hand, and relax, brushing teeth, washing face, drinking actions, and reaching movement.	Maximum, amplitude, mean, root mean square, mean absolute value, jerk, approximate entropy, dominant frequency, median/mean frequency, difference absolute standard deviation value, energy, interquartile range, log detector, standard deviation value, skewness, linear prediction coefficient, zero crossing, slope sign change, spectral entropy, simple square integral, waveform length, auto-regressive coefficient, maximum-to-minimum drop in power density ratio, complexity, frequency ratio, mean absolute value slope, power spectrum deformation, power spectral density fractal dimension, power spectrum ratio, v-order features, variance of central frequency.	1) Can provide quantitative data related to muscle activity. 2) Aids in targeted training by identifying damaged muscle groups.	1) It requires a smooth skin surface and is sensitive to environmental factors. 2) High technical requirements require professional signal processing.
Visual sensor	Markers are placed on the third metacarpophalangeal joint of the hand, the ulnar styloid process of the wrist, the lateral epicondyle of the elbow joint, the middle of the left and right acromion, the upper part of the sternum, the forehead, the upper and lower edges of the glass. [70], [73]	Action of picking up the full water and the empty water glass is carried out respectively at low, medium, and high table heights.	Jerk, velocity (mean, max, min, time to max), angles, aperture (max distance, time to max distance, standard deviation), curvature (straight line distance, path length, radio), movement time, number of motor units, peak angular elbow velocity, peak hand velocity, time relative to peak hand velocity, arm abduction, and trunk displacement.	1) Non-contact can reduce patient discomfort. 2) Visualization. Movement can be observed more intuitively. 3) Enables multidimensional evaluation, capturing information on multiple joints or planes simultaneously.	1) High work environmental requirements, which may increase the use cost. 2) Limited by field of view and occlusion errors. 3) Accurate sensor calibration and positioning are needed.



(a) (b) (c)

Fig. 6. Bio-electrical signal sensors: (a) sEMG sensor [75]. (b) EEG sensor [76]. (c) MMG sensor [77].

was designed based on the sEMG data and the movement of the robotic arm. In addition, sEMG sensor could also be used in combination with other sensors. Meng et al. [65] placed 5 sEMG sensors, 5 accelerometers, and 5 gyroscopes on the side of the affected upper limb to jointly collect motion parameters, such as the speed, direction, and joint angle. Then, these were used to estimate the Brunnstrom Recovery Stage. Unlike the use of sEMG sensors, EEG sensors and MMG sensors are used to collect the bio-electrical activities of the cerebral cortex and mechanical vibration signals of muscles [74], [78]. For example, Lassi et al. [79] used the EEG sensor to collect the cerebral cortex bio-electrical signals from stroke survivors within 72 hours after their stroke. The features of spectral and connectivity domains were then extracted from these signals to classify the stroke patients, achieving an accuracy of 85%. Moreover, an MMG sensor was utilized to classify hand tasks in the FMA scale [74].

There are several advantages of using bio-electrical signal sensors for the upper limb impairment assessment. For example, it can provide real-time feedback and detect the subtle muscle activity information, thereby enhancing the accuracy and reliability of the system. However, there are also evident limitations. Firstly, the cost of these sensors is high [80], which hinders their extensive use. Secondly, the processing of these sensor signals requires a high level of expertise. In addition, the high requirements of sEMG sensors and EEG sensors on the skin contact and environment humidity also affect their applications [74], [78], [81].

In short, bio-electrical signal sensors can provide accurate information about the brain activity, muscle ability, and motor control, which are of great significance for establishing an objective, quantitative, and real-time upper limb impairment assessment system. However, the limitations when using them also need to be considered.

D. Visual Sensors

The final category of sensors utilized in the upper limb impairment assessment systems is the visual sensor, encompassing markers and cameras. It can be utilized to capture the three-dimensional positions of different body parts, subsequently allowing the extraction of the upper limb motion trajectories and postural changes. Then, kinematic indicators, such as joint angle and range of motion, can be analyzed from this information. Finally, the motion ability of the upper limb can be estimated based on these indicators.

Some studies have used visual sensors [82], such as the motion capture sensor systems, consisting of a camera and multiple markers attached to the body. These systems are able to track the position of the patient in real-time and capture the movement at marker points. In addition, the Kinect sensor is used to provide depth perception function [83]. In the upper limb impairment assessment systems, it can be used for the skeletal tracking to analyze the hand movement and upper limb joint angle information. It is evident that visual sensors can collect a wide range of kinematic and physiological data.

One notable difference between visual sensors and other sensors in the upper limb impairment assessment systems is their non-invasive nature and without the complex equipment that needs to be attached to the patient [84], [85]. This characteristic significantly minimizes the influence of external factors on the motor performance of patients, thus enhancing the reliability and accuracy of the systems. Therefore, visual sensors have significant potential in facilitating the assessment of the motor performance in the upper limbs of stroke patients. Nonetheless, it is important to acknowledge the inherent limitations of visual sensors, including their inability to capture subtle motions and challenge in dealing with occlusion issues [84]. These may reduce the accuracy and reliability of the systems, necessitating further improvement in the experimental environment and system precision. To address these limitations, researchers have commonly employed a complementary approach by integrating supplementary sensors, such as IMUs, to enhance the functionality and performance of the impairment assessment systems.

E. Multi-modal Fusion

Multi-modal fusion of multiple types of sensors in the field of stroke assessment integrates information from different sensors to gain a comprehensive and multi-dimensional understanding of the patient's rehabilitation status [86], [87]. In [87], Lv et al. designed an information fusion algorithm to combine heartbeat, kinematics, and height information for comprehensive analysis to achieve more accurate detection of falls in stroke patients. In addition, Li et al. [88] used a decision fusion method to calculate weighted scores for kinematic scores and sEMG scores, which improved classification accuracy and enhanced clinical relevance. Although the introduction of multi-modal fusion has advanced the development of impairment assessment, it also brings some challenges, such as data heterogeneity and feature fusion. However, Lv et al. [89] improved the multi-modal features fusion by representing data from different modules as low-dimensional semantic vectors, providing a potential solution for current challenges. In summary, the potential of multi-modal fusion from various sensors offers more effective rehabilitation assessments and personalized rehabilitation plans for stroke patients.

III. Quantitative Impairment Assessment Methods

The use of quantification algorithms aims to map the collected data into a quantified indicator to represent the motor function of patients. Upper limb quantitative impairment assessment algorithms can be classified as the model-based method and model-free method (also known as the kinematic indicator-based method) [74], [90], [91]. Model-based method typically involves using a large amount of data collected from sensors to establish a data-driven model. Subsequently, based on the relationship established within the model between motion data and medical scales, it can be used to generate universally accurate scores for any type of the motion. Thus, it has the ability to analyze more comprehensive motions. Differently, model-free method is based on a specific physiological or kinematic index to directly quantify the sensor data.

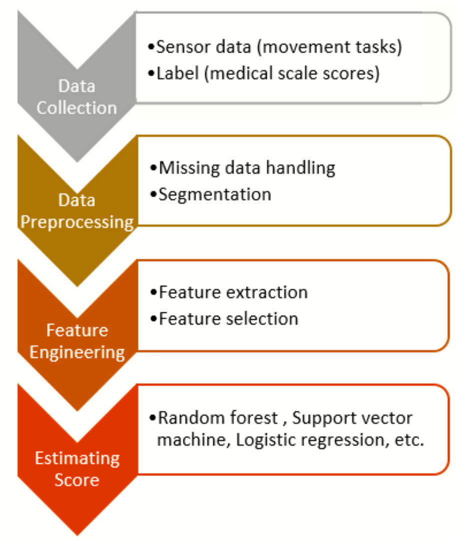


Fig. 7. Diagram of machine learning-based data analysis.

A. Model-Based Quantitative System

Model-based methods can be divided into two categories: those using traditional machine learning algorithms and those based on deep learning algorithms. Machine learning algorithms usually require manual feature extraction, while deep learning algorithms tend to automatic feature learning, reducing the need for manual feature extraction. Moreover, they are often used in conjunction with scores from medical scales to derive an estimated quantitative value of the upper limb impairment from the sensor data. In addition, feature optimization and algorithm parameter optimization methods are also important parts of the model-based quantification system. The performance, advantages and limitations of these model-based algorithms are shown in Table III.

1) Algorithms Requiring Manual Feature Extraction: Fig. 7 shows the schematic diagram of the data analysis process based on machine learning algorithms. The systems first preprocess the data obtained from the sensors. Then, they combine medical scale scores as labels and perform data segmentation. Finally, systems extract features from the data and undergoes repetitive training and optimization, thereby accurately obtaining estimated scores [57], [91]–[93]. The most commonly used machine learning algorithms are including random forest (RF) [92], support vector machine (SVM) [57], and logistic regression (LR) [91], etc.

a) RF-based model: RF serves as a powerful tool to help clinicians or rehabilitation specialists automatically and accurately assess the upper limb motor function of patients. In detail, RF performs prediction and classification tasks by building multiple decision trees [94]. Each of the decision trees is trained independently, and the diversity of the model is enriched by randomly selecting sample subsets and features [95].

RF has been widely used in the upper limb automatic impairment assessment systems. For example, Patel et al. [51] combined RF and linear regression to evaluate the FAS scores of patients on eight motor tasks. This study used multiple time-domain features for each axis of each accelerometer and the Relief F feature selection algorithm, achieving the best RMS error range between 5% and 6% in the laboratory environment. Moreover, multiple algorithms divided the overall assessment process into multiple parts for scoring, resulting in an overall improvement in accuracy. After using the RF algorithm to classify each task, the combination of linear regression [64] or RF [19] to estimate the total score will further improve the accuracy of the system. These studies show that RF combined with medical scales for quantitative impairment assessment has broad application prospects.

Impairment assessment systems based on RF can also perform well when the dataset used is large [96]–[98]. This is because it only needs to consider part of randomly selected features on each node, which can make it more effective when dealing with high-dimensional data [95], [99]. Furthermore, RF actually can be treated as an ensemble learning scheme that aggregates several predictions to reduce the variance and improve the accuracy of the system [94], [100]. However, employing a large number of trees and deep trees would cost substantial computational resources for model training and prediction [99]. In short, RF used in the automatic upper limb quantitative impairment assessment system can help medical experts to more accurately assess the upper limb function of patients.

b) SVM-based model: SVM is one of the most commonly used machine learning algorithms because of its excellent classification ability. It classifies the data by mapping the features of the input data to a higher dimensional feature space [101] and finding the hyperplane where these features have maximum classification distance [102]. In [45], SVM combined with Oxford Grading Motor Scale were used to estimate the muscle movement grade of patients. In this study, according to the time domain and frequency domain signal features obtained from the accelerometers, the muscle movement ability was divided into two levels (dependent and antigravity represent poor and good movement ability), and achieved a testing accuracy of 0.77 in the clinical environment. However, SVM only can directly solve binary classification problems, one-against-one or one-against-all strategy is usually needed when we want to solve multiclass classification problems, which may increase the complexity of the model.

c) LR-based model: There are also some of the researches used LR, which is a common classification algorithm. It is based on a probabilistic model that allows assessment and prediction of the upper limb function by establishing the relationship between input features and classification results [103]. Werner et al. [91] used the ARAT scale and LR classifier to automatically score 19 motor tasks performed by patients, and the final weighted accuracy rate was about 80%. LR is used because its results are easy to interpret and computationally efficient, and it can explain the degree and direction of the influence of different characteristics on the upper limb function, and provide help for the design of personalized rehabilitation programs. However, its linear implementation limits its application in nonlinear relationships. LR has the advantages of strong interpretability and high computational efficiency, and can be used to predict and assess the level of the upper limb function of patients. However, it is also necessary to pay attention to the data distribution in practical applications.

d) Others: There are some other machine learning algorithms that have also been applied to the upper limb quantitative impairment assessment systems. For example, Li et al. [104] designed a VR-based upper limb rehabilitation system after stroke, and used multilayer perceptron (MLP), radial basis function network (RBFN), SVM, and decision tree (DT) to quantitatively evaluate the motion performance. It was finally found that MLP performed best on their system, achieving 92.72% accuracy. In addition, longitudinal mixed effect model with Gaussian process prior (LMGP) method was used to realize the automated assessment of Chedoke Arm and Hand Activity Inventory (CAHAI) [105]. LMGP exhibits remarkable flexibility across diverse participants and time slots, as demonstrated in experiments with both acute and chronic patients [105]. Moreover, considering extreme learning machine (ELM) does not require iterative training to adjust weights and has a fast training speed, it has also been employed by a portion of study [58], [106]–[109].

2) Algorithms With Automatic Feature Extraction: Models using such methods are usually implemented based on deep learning. Its workflow is expressed in Fig. 8. The data collected from sensors and medical scales are normalized in the preprocessing phase. Then, the deep learning algorithm will automatically find the characteristics of the data and establish the relationship between the input and output. It can be used not only for quantitative scoring in combination with medical scales, but also for activities classification [28], [52]. The principle of deep learning algorithms is to simulate the human nervous system to learn and discover complex nonlinear relationship between sensor data and medical scale scores [110]. The most commonly used deep learning algorithms are including deep neural network (DNN), convolutional neural network (CNN) [47] and long short-term memory (LSTM) [111], [112].

a) DNN-based model: DNN refers to a deep neural network formed by interconnecting multiple layers of artificial neurons [113], [114]. The neurons in each hidden layer process the input through a nonlinear activation function, so that DNN can learn and discover the nonlinear relationship between the input and output. It can automatically obtain more complex and abstract features through learning, resulting in more powerful representation when dealing with complex tasks. For example, Hossain et al. [115] used a DNN model with tree hidden layers, rectified linear unit (ReLU) and sigmoid function as the activation function to assess sensory

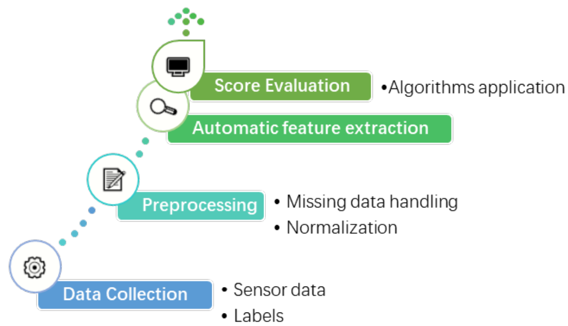


Fig. 8. Diagram of deep learning-based data analysis.

impairment after stroke and finally obtained 85.6% accuracy. Similarly, DNN was also used to estimate Brunnstrom scale scores after stoke [116]. In sum, DNN can automatically extract features and classify them from the raw sensor data, and it also has a good performance in the study of quantitative impairment assessment after stroke [117], [118].

b) CNN-based model: CNN could achieve excellent performance in image classification and visual data recognition [117]. In [119], sequential data was encoded into images for the application of CNN on time-series sensor data. By using convolutional and pooling layers, CNN is able to efficiently extract image features for high-accuracy classification and identification of upper limb functions [28], [47]. However, CNN also has some limitations, such as demand for data samples and consumption of computing resources. Furthermore, it may also be considered as a black box [28], since the implementation process is less explainable.

c) LSTM-based model: LSTM is mainly for processing sequence data [120], [121], which is able to capture the temporal features of the motion. LSTM is with the gating mechanism, including four parts: the input gate, output gate, forget gate, and cell state [120]. The gate units allow the network to selectively forget and update the information through the sigmoid function and dot product operation [112], [120], [122]. It can solve the long-time dependency issues in the recurrent neural network, so that it can better handle the time-series data in the stroke impairment assessment [112]. Due to the advantages of LSTM in processing time-series signals, it has been used to distinguish the presence of the spasticity as part of a quantification system [111]. In addition, Xu et al. [112] used an LSTM-based model to predict the grip strength of patients, enhancing the ability of the model to deal with long-term dependencies. LSTM helps to more accurately process data in stroke impairment assessment studies and exhibits potential in quantification systems and predictions.

In summary, deep learning algorithms have been extensively studied in upper limb impairment assessment systems as powerful tools. They are capable of establishing complex nonlinear relationships, providing accurate predictions and evaluation results [28], [47]. However, in practical applications, their complexity and computational requirements need to be fully considered, and the network structure and parameters should be selected reasonably.

3) Feature Optimization: Feature optimization refers to the selection of the most representative and relevant features from the large amount of the collected motion data to evaluate the system. This is a critical step that contributes to the accuracy and reduces the computational complexity of the system [123]. The specific method is to select the most relevant features through some feature optimization algorithms, reduce the dimension of the data and the redundant information, and help prevent the occurrence of over-fitting problems.

In the common feature optimization process, various algorithms and techniques can be used, including Relief F, Principal Component Analysis (PCA) dimensionality reduction, and correlation analysis. In practical applications, the Relief F algorithm [124] updates feature weights by calculating the differences between sample features and the nearest neighbors from the same class and different classes. It uses this information to measure the contribution of features to the classification [51], [58]. Generally, the Davies-Bouldin (DB) cluster validity index [125] method was also used at the same time to add one feature at a time according to the feature ranking obtained by the Relief F algorithm and select the most suitable feature amount [51]. Moreover, PCA extracts main features from high-dimensional data by calculating eigenvectors and eigenvalues, and reduces dimensions to achieve feature optimization [123], [126]. The last commonly used feature optimization method is the correlation-based feature selection algorithm [127]. It can efficiently select features that are highly correlated with the target class but have low correlations with each other by evaluating the correlation between features and the target class, as well as the correlation among features, using techniques such as t-tests or analysis of variance [50].

Accordingly, it can be seen that these methods can help identify which features are more crucial for the upper limb impairment assessment, thereby enhancing the system's robustness and predictive capability. It is essential to emphasize that feature selection optimization is a complex and challenging task, and the rational selection and optimization of features require considering the specific requirements and research objectives of the system.

4) Algorithm Parameter Optimization: During the process of the upper limb impairment assessment using machine learning and deep learning, some parameters that need to be set in advance can significantly affect the performance of the system. Algorithm parameter optimization can enhance the accuracy and robustness, ensuring the system to provide more reliable and precise results for evaluating upper limb motions in post-stroke patients. For example, Patel et al. [51] verified the performance of different numbers of trees in RF. They found that using 50 trees significantly improved the performance of the system compared to using 10 or 20 trees, but there was no substantial change when using 100 trees. They presented the effect of different numbers of trees in RF on the performance of the upper limb impairment assessment system. In addition, hyperparameters of SVM also can be optimized using the grid search [128], [129]. However, it should be noted that algorithm parameter optimization may require multiple attempts and adjustments. Additionally, the algorithm parameter optimization also depends on the characteristics of the data and the type

TABLE III
COMPARISON OF MODEL-BASED IMPAIRMENT ASSESSMENT ALGORITHMS

Category	Method	Performance	Advantage	Disadvantage
Machine Learning	RF-based [51]	rms error range 5%-6%.	High robustness, ensemble learning.	Tedious parameter adjustment.
	SVM-based [45]	Testing accuracy 0.77.	Effective in handling high-dimensional data, strong non-linear classification capability.	Weak multi-categorization ability.
	LR-based [91]	Weighted accuracy rate 80%.	Simple, easy to interpret.	Poor performance in fitting non-linear relationships.
	ELM-based [58]	Coefficient of determination $R^2 = 0.918$.	Simple to implement, fast to train.	More sensitive to noise.
	MLP-based [104]	Accuracy rate 92.72%.	Powerful fitting capability.	Poor interpretability.
Deep Learning	DNN-based [115]	Precision of 85.6%.	Suitable for complex models.	Long training time, easy to over-fitting.
	CNN-based [117]	Accuracy of 88.87% on naturalistic data.	Good at handling image data.	Sensitive to variations in input data.
	LSTM-based [104]	Coefficient of determination $R^2 = 0.9023$.	Suitable for sequential data.	Potential issues with vanishing gradients and a high number of parameters.

of the algorithm, so it needs to be optimized according to the specific situation.

B. Model-Free Methods

Although model-based methods for quantifying the upper limb motion ability have been well-verified [71], there are also limitations in certain aspects. For example, there will be noise introduced due to human scoring as labels, a large amount of data is required for model training and combining medical scales can lead to a ceiling effect [58], [130]. Unlike model-based methods, model-free methods could directly quantify the upper limb motor function based on the patient kinematic or physiological indicators. Thus, model-free methods could addresses the limitations of model-based methods in terms of label noise, large data requirements and ceiling effects. However, its clinical effectiveness has not been extensively verified. The most commonly used methods are threshold count, gross motor score, and personalized indicators.

1) Threshold Count: Threshold count [131] method provides a systematic approach to assess the upper limb motor performance based on predefined thresholds [132]. Its fundamental principle is to quantify the number of successful motor actions performed by the patient above predetermined thresholds. It can be defined based on various factors, such as acceleration, magnitude, motion duration, or range of motion. By setting specific criteria, clinicians can objectively measure and track the motor ability of patients through threshold counts [131]. Activity counting based on acceleration was originally proposed based on acceleration data after the effect of the gravitational acceleration was removed. Specifically, De Lucena et al. [133] used a threshold of 0.017g to classify the acceleration data. If the average acceleration in each 1s window exceeded this value, it was recorded as the existence of activity and marked as 1, otherwise, it should be 0. Finally, the degree of injury on the affected side of the upper limb was quantified based on the imbalance of activity counts on both sides of the upper limbs. Another type of the threshold count method is based on vector magnitudes. It involves calculating the magnitude of the acceleration data on three axes of an accelerometer within the same time period. This is done by squaring the acceleration values on each axis, summing them, and then taking the square root to obtain the vector magnitude [134]. The vector magnitude ratio of the two limbs is used to quantify the difference in the intensity of the motion between the affected limb and normal limb after stroke.

Quantitative assessment of the upper limb impairment achieved by the threshold count method has several advantages. First, it provides an objective, standardized measure that minimizes subjective bias. Second, this method is relatively simple and suitable for clinical and daily use. Additionally, it has a high sensitivity to pick up subtle changes in motion patterns that may not be easily discernible through visual observation alone. However, this also leads to its low specificity, and choosing an appropriate threshold is challenging [130], [132]. In short, the threshold count method is a valuable method for the quantitative assessment of the upper limb impairment in stroke patients. By setting predefined thresholds, this method provides a standardized and objective measure of the upper limb impairment. Although it has advantages, such as objectivity and comparability, its limitations also require careful consideration and validation when applying the method in the clinical practice.

2) Gross Motor Score: Different from the threshold count method, the gross motor score defines the presence of the activity by analyzing the amount of the change in the yaw and pitch angles of the upper body motion within a window. It is based on an important assumption that during the activities of daily living, the position of the wrist is mainly determined by the sagittal plane and upper part of the waist [135], [136]. In the real application, the specific implementation process of this method is to use the Madgwick algorithm to obtain the yaw angle and pitch angle information from the sensor data. Then, the motion in which the total change of these two angles is greater than 30° within a window, and the absolute pitch angle of the forearm is within ±30° is defined as a functional motion, marked as 1, otherwise, it is 0. The procedure that follows is similar to the threshold count method, quantifying the severity of the affected limb by counting the difference in the number of functional motions performed by the limbs on either side of the same motion [130], [137].

Gross motor score method extends the measurement of the functional motion of the arm, which cannot be done with the activity count method [137]. Limiting the measurement to functional motions only can effectively reduce the impact of the non-functional motion data on the impairment assessment [138]. This is because non-functional motions, such as unintentional arm swings during walking, do not significantly differ in the motion data between the affected and unaffected limbs. However, this method also has an obvious disadvantage that it is not very sensitive. This can cause the system to miss some smaller motions. Moreover, according to [138], it can also be concluded that the accuracy of the gross motor score is 50% to 60%, which is lower than the 72% accuracy of the activity counts [132]. To sum up, the gross motor score method quantitatively assesses the upper limb motor function in stroke patients by analyzing yaw and pitch angles within specific criteria. It has the ability to distinguish between the functional and non-functional motions, but there are also accuracy and sensitivity issues that require further research and optimization.

3) Personalized Indicators: Both the threshold count method and gross motor score method involve the conversion of kinematic indicators collected from sensors to indirectly derive quantitative scores for assessing the upper limb function. The practice of directly designing personalized indicators based on the sensor data for the quantitative impairment assessment can be referred to as the personalized indicator evaluation. Typically, it entails designing quantitative indicators by leveraging the disparities in physiological or kinematic values obtained from the sensor data between the unaffected limb and the limb affected by stroke.

Some studies have designed some personalized indicators based on the asymmetry of the upper limbs, such as amplitude asymmetry [133], jerk asymmetry [133], and mobility difference [52]. In [133], two new indices, namely the acceleration amplitude asymmetry index and jerk asymmetry index, were designed. The calculation method for the first index was based on the average magnitude of the acceleration obtained from accelerometers on both sides of the limbs. By taking the difference between the values of the two sides divided by their sum, a value ranging from -1 to 1 was obtained. This index quantified the motor performance of the limb affected by stroke. Then, the calculation method for the jerk asymmetry index was similar to the first index, but it utilized the average magnitude of the jerk (rate of change of acceleration) on both sides of the body. Similarly, it yielded an index ranging from -1 to 1. The mobility index was developed based on the asymmetry of the frequency and amplitude of bilateral limb motions to create a range index to describe the upper limb ability [52]. Moreover, Huang et al. [67] designed an index based on the upper limb joint angle that is different from the aforementioned kinematic parameters. By using the Euler angle or quaternion method, the inertial sensor data was converted into the joint angle change data, and then the range of joint motion of the patient was directly compared with that of the normal human body, and a new index describing the motion ability was obtained.

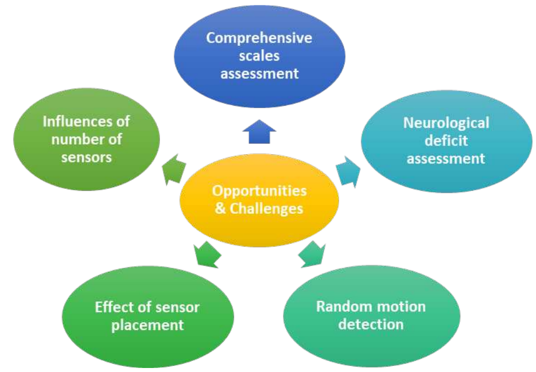


Fig. 9. Opportunities and challenges in the upper limb impairment assessment.

Since these indicators are derived directly from kinematic or physiological parameters, they not only provide quantitative measurements but also offer more precise descriptions of the motor function. However, due to the disadvantages of the limited indicators used, they may not provide a comprehensive assessment of the upper limb impairment. Moreover, the limited number of studies on these methods does not establish their effectiveness for the widespread use. Therefore, further validation and standardization research is still needed to determine their reliability, sensitivity, and clinical application prospects.

IV. OPPORTUNITIES AND CHALLENGES

Although the automatic upper limb impairment assessment system has made great achievements, some emerging issues (as shown in the Fig. 9) also need to be further explored, such as comprehensive assessment of medical scales, neurological deficit detection, random motion detection, the effects of the sensor placement, and the influences of number of sensors. In this section, we first describe these directions and current developments, and potential challenges and ideas are then illustrated.

A. Assessment of Medical Scales

Medical scale is currently recognized as the gold standard that can quantify and estimate the severity of stroke more accurately. [139], [140]. Commonly used medical scales are NIHSS, FMA, WMFT, ARAT, etc. Measures included in these scales are mobility of joints in the upper limbs, motor coordination, and sensory abilities. Although there has been a lot of studies on simulating the tasks on the medical scale by measuring the motion parameters and physiological indicators of patients based on sensors, how to fully and automatically evaluate all the tasks in the scale is still a challenge. Most of the existing works are based on the evaluation of part of tasks in the scales.

Since only a small number of motion tasks can be detected using accelerometers [141], Otten et al. [57] combined a variety of sensors to expand the range of the collected data to complete more FMA scale detection tasks. They used a Kinect sensor to detect the joint angle information, an IMU to detect arm and wrist rotation and shaking, and a bend sensor and pressure sensor to measure the hand motion and grip strength. Finally, 73% of the motor tasks in the upper limb part of FMA was achieved. However, the task of assessing sensory abilities in the upper limb of the scale remains a challenge. For example, Hossain et al. [115] used exoskeleton robots and machine learning algorithms to automate the evaluation of proprioception. In the experiment, the robotic arm moved one arm, and then the patient was asked to use another arm to follow a felt trajectory. After that, the performance of the arm position matching task was analyzed from the trajectories and motion data of the two movements. Finally, the proprioceptive sensory abilities as mentioned in the Nottingham Sensory Assessment [142] and Wrist Position Sense Test [143] could be measured automatically. However, the measurement of muscle reflexes and tactile perception involved in the most commonly used scales, such as NIHSS and FMA, still needs further exploration.

B. Assessment of Neurological Deficits

The purpose of using medical scales in combination with machine learning or an automated upper limb impairment assessment system based on kinematic metrics is to analyze the motion data from patients and obtain a quantitative measure of stroke severity. However, the impact of neurological deficits caused by stroke on the kinematic level is often overlooked, which would potentially influence the final results. This is because different neural-muscular mechanisms may produce similar motions [69], which may not have significant differences in sensor data representation. Haley et al. [144] employed magnetic resonance imaging (MRI) technique to directly analyze the neurologic system of stroke patients, demonstrating that the integrity of white matter in the corticospinal tract during arm motion is correlated with the severity of post-stroke motor impairment. This approach allows for direct analysis of the impact of neurological deficits during patient motion. Pan et al. [69] also proposed a solution by using multiple sEMG sensors placed on different muscles of the upper limb to collect muscle activation signals, thereby directly expressing the muscle synergies. However, an obvious issue is that the sensors used in these methods are relatively expensive and require professional knowledge to process the signal. Therefore, further research is still needed to make these methods more accessible and user-friendly.

C. Random Movements Detection

The detection of random movements remains a major challenge in this field. Current research efforts primarily focus on quantifying prescribed movements specified within medical scales using sensors and machine learning algorithms. These studies primarily evaluate the specified tasks within a clinical environment. Additionally, some studies aim to quantify movements based on daily activities, such as drinking or dressing, thus expanding the range of environments in which assessments can be conducted [65], [145], [146]. For example, Meng et al. [65] quantitatively evaluated the three actions of brushing teeth, washing face, and drinking water based on the Brunnstrom Recovery Stage scale, accelerometer, and sEMG. However, these studies are still limited to specific ranges of the motion and are unable to achieve the detection and quantification of random movement tasks. While some research works have employed quantification methods based on threshold count or gross motion analysis, which do not restrict the types of tasks performed by patients, there is still significant room for accuracy improvement.

Therefore, it is necessary to develop robust and reliable methods to detect and quantify random movements in stroke patients. This will expand the scope of the impairment assessment beyond the clinical setting, including real-world scenarios. By capturing and analyzing movements during daily activities, researchers can gain a more complete picture of the functional capabilities of patients and develop rehabilitation strategies.

D. Effect of Sensor Placement

Sensor placement remains a challenging issue for the accuracy and reliability of impairment assessment systems. Different sensor placement can lead to varying results, emphasizing the critical importance of choosing appropriate positions to obtain the accurate data [58]. For instance, sEMG sensor is a commonly used sensor for measuring muscle bio-electrical activity. However, placing the sensor at different locations on the muscle may result in changes of signal strengths and spectral characteristics, leading to unstable measurement outcomes. Similarly, other sensors, such as accelerometers, gyroscopes, and force sensors, can be utilized for quantifying the upper limb movement and strength. Nonetheless, the placement of these sensors also significantly influences the measured results. For example, installing an accelerometer on the wrist, forearm, or shoulder can yield different measurements of motion trajectories and amplitudes. To address the effect of the sensor placement, researchers typically conduct extensive experiments and analysis to determine the optimal positions [47]. This involves comparing measurement outcomes from different placement and considering the specific characteristics of stroke patients. Therefore, selecting appropriate sensor positions is crucial for the accuracy and reliability enhancement of the automatic quantification assessment for the upper limb impairment after stroke. Researchers need to consider the characteristics of different sensors and the specific conditions of stroke patients when choosing the optimal sensor placement. Further research and technological advancements will contribute to overcoming this challenge and advancing the field of stroke rehabilitation.

E. Effect of Number of Sensors

The choice and placement of sensors have been discussed, and it is worth noting that the performance of the system can also be influenced by the number of sensors [58]. When the number of sensors is sufficient, it can potentially provide more comprehensive motion data, thereby enhancing the sensitivity and accuracy of the system. For example, by placing sEMG sensors at different muscles of the upper limb, more motion data can be collected to directly express muscle synergy [69], [123]. However, increasing the number of sensors can also lead to the increase of the system complexity, requiring more resources to analyze and process the data. Furthermore, Patel et al. [51] utilized multiple accelerometers to derive the FAS score. Through experimentation, it was observed that adding more sensors seemed to benefit the performance of the system when detecting activities involving more than four motion tasks. However, beyond a certain number of sensor quantity, the accuracy was found to be negatively affected. Therefore, it is necessary to balance sensitivity, accuracy, complexity, and resource investment when selecting the number of sensors. At the same time, further research can explore how to improve the performance of the system and the feasibility of the application by optimizing the arrangement and selection of sensors.

V. Conclusion

This study provides a comprehensive review of sensor-based systems for post-stroke upper limb impairment assessment, focusing on the use of sensors and the analysis of quantification algorithms. The four types of sensors used in this field, the process of using the quantification algorithms, the latest progress, and its limitations are then presented to provide a potential reference for future research. Finally, some potential opportunities and challenges are introduced, including testing the comprehensiveness of medical scales, neurological deficit assessment, random motion detection, the study of the influence of sensor placement and the number of sensors.

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