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A Review of Robot-assisted Hand Spasticity Assessment

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***Abstract*—Spasticity is a common neuromuscular abnormality following upper motor neuron lesions. Conventionally, spasticity is assessed through manual clinical scales, which have limitations due to the subjectivity involved. The development of rehabilitation robotics introduced new solutions to this problem, producing novel robot-assisted spasticity assessment approaches. In this paper, we present the current state and challenges of robot-assisted hand spasticity assessment (RAHSA), based on a review of instrumented clinical scales, biomechanical and neurophysiological measures, and medical imaging methods for upper extremity spasticity assessment between January 2000 and February 2023. The characteristics of hand anatomy and spasticity symptoms make it challenging to develop RAHSA approaches and corresponding robotic systems. Although the combination of hand robots and instrumented assessment methods has evoked studies on RAHSA, more research is needed on the new assessment approaches fusing neurological and non-neurological measures and novel robotic systems specifically designed for hand spasticity assessment.**

***Index Terms*—Spasticity, robot-assisted assessment, rehabilitation robotics, upper extremity, hand.**

I. Introduction

Spasticity is a common complication following upper motor neuron (UMN) lesions, referring to abnormal muscle activity during passive or active limb movement [1, 2]. The cost of caring for a patient with neurological disorders is likely to quadruple as a result of spasticity, so the management of spasticity is significant in the treatment of UMN lesions [3]. Assessment is a crucial part of managing spasticity, while widely-used conventional assessment approaches are typically time-consuming, labour-intensive, and reliant on subjective judgments; therefore, it is anticipated that new rehabilitation technologies will make breakthroughs in lower cost, fast, and objectively quantified spasticity assessment [4].

Robot-assisted assessment is regarded as a promising solution to enhance and potentially reform existing assessment approaches. Although numerous rehabilitation robots have been developed for the recovery of limb functions following UMN lesions [5, 6], the functionalities for assessing spasticity, particularly hand spasticity, remain relatively rare in existing rehabilitation robots. This paper aims to review prior research on robot-assisted hand spasticity assessment (RAHSA), analyse the typical combination of instrumented spasticity measures and hand rehabilitation robots, and finally identify promising directions for future research on RAHSA.

A. Definition of Spasticity

It is crucial to clarify the definition of spasticity before discussing robotic technology for spasticity, as the definition states the essential characteristics of spastic symptoms, thereby indicating measurement requirements of spasticity [7]. A widely accepted definition of spasticity is "*a motor disorder characterised by a velocity-dependent increase in the tonic stretch reflexes (muscle tone) with exaggerated tendon jerks, resulting from hyper-excitability of the stretch reflex, as one component of the UMN syndrome*", proposed by Lance in 1980 [8]. However, this definition has been challenged for many years [9-11]. On the one hand, the velocity-dependent increase of muscle tone is not an absolute feature of spasticity [9]. On the other hand, clinically, spasticity is used as an umbrella term for multiple features of UMN syndrome rather than solely referring to an increase in stretch reflexes [10, 11]. Given these debates, in 2005, the Support Programme for Assembly of a Database for Spasticity Measurement (SPASM) consortium proposed that spasticity should be used as a collection of many positive symptoms of the UMN syndrome, and redefined spasticity as "*an emergent feature of disordered sensorimotor control, resulting from an UMN lesion, presenting as intermittent or sustained involuntary activation of muscles*" [10]. Specifically, the symptoms of spasticity include increased reflexes, altered muscle tone, spasms and clonus, spastic dystonia, and abnormal co-contraction [11].

Patients with hand spasticity often encounter difficulties in finger movement and may even experience a complete loss of hand function. Spastic finger muscles may demonstrate abnormal muscular reflexes and hyperactivity, resulting in tightness, stiffness and clenched fist [2]. Assessing spasticity in the hands is more challenging than in other upper extremity joints due to the complex anatomy and dexterity of hands [12, 13]. For example, fingers suffering from clenched fists remain closed due to excessive finger flexion. Both intrinsic and extrinsic muscles contribute to this abnormal flexion; clenched fists caused by different muscle groups may show distinctive symptoms [14].

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B. *Objectives and Framework*

Numerous approaches have been proposed to evaluate spasticity through clinical scales, biomechanical parameters, neurophysiological features and medical images [15-20]. Although some instruments were developed to assist manual assessment, as will be reviewed in this paper, with the advancement of research on spasticity assessment approaches, the requirements of instruments are getting higher to accurately and robustly record multidimensional data. Robotic systems are typically integrated with multiple sensors of kinetic information, accurate motor units, and powerful computation ability, so that they can meet the increasingly challenging functionality requirements of novel assessment approaches [21].

A systematic review has been conducted to investigate robot-aided systems for improving the assessment of upper limb spasticity [21]. The review primarily focused on the system and function design of robotic devices but did not give a full picture of existing spasticity assessment approaches. Another systematic review scoped technology-assisted assessment of upper and lower extremity spasticity [4], providing a statistical analysis of the main techniques used in spasticity assessment. However, neither reviews addressed the performance of instrumented assessment methods in relation to spasticity pathophysiology and clinical requirements, and their applicability to hand spasticity [7]. Moreover, the research progress of RAHSA has not received specific attention in any prior review.

In this review, we aim at filling in these gaps by reviewing robot-related assessment approaches for upper extremity spasticity and emphasising the emerging work on hand spasticity in the past two decades. Given the limited studies on RAHSA, solely concentrating on RAHSA might result in a noncomprehensive understanding of the available spasticity assessment approaches to combine with robots. Therefore, we explore the robot-assisted assessment approaches for upper limb spasticity with the aim of identifying applicable techniques for hand spasticity. This strategy provides a wider spectrum of knowledge to grasp the research gaps in RAHSA and outline RAHSA's future development.

The main text is structured into four sections. Section II presents the search and selection method and the statistics of the previous research. In Section III, we describe the combination of common assessment approaches for spasticity and robotic technologies. Following that, prior studies on RAHSA are presented in Section IV from four perspectives: robotic devices, assessed hand joints, assessment approaches, and experimental evidence. In the Discussion section, we analyse the main challenges of RAHSA and discuss the prospects for improvement in future research.

II. Search and Review Methods

A. *Search Strategy*

The search and review method was conducted as the flow diagram in Fig. 1 [22]. A general search was performed in IEEEX, PubMed, Scopus and Web of Science. The period

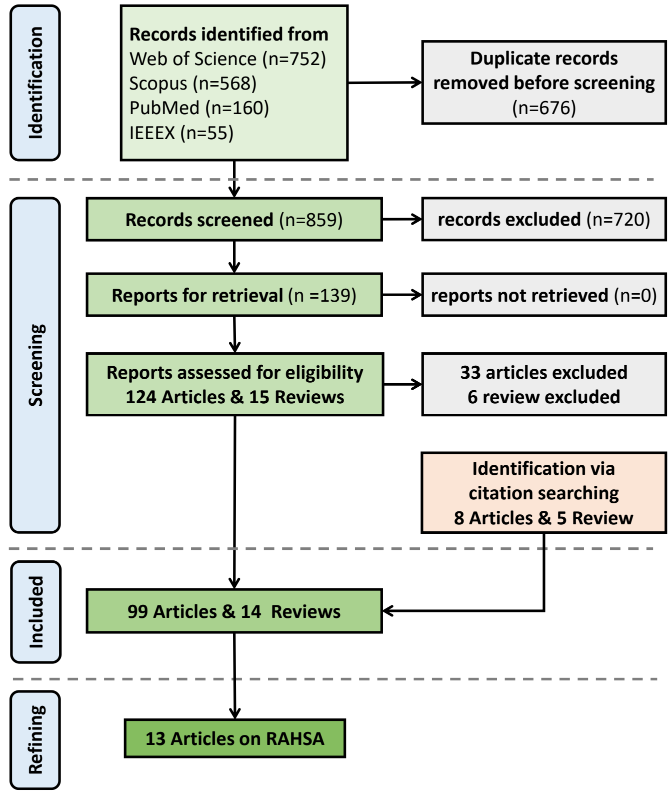


Fig. 1. Flow diagram of references search and selection.

covered in the search is from 2000 January to 2023 February. Only English articles published in conferences or journals were included. The search terms were the combinations of the following keywords with Boolean operators and wildcard symbols:

a. *assess** OR *measure** OR *evaluat**
b. *spas**
c. *hand* OR *finger* OR *wrist* OR *upper limb* OR *upper extremit**
d. *EMG* OR *electromyography* OR *electrophysiolog** OR *neurophysiolog**
e. *biomechanic** OR *mechanic**
f. *ultrasound* OR *elastography*

The query string, a AND b AND c AND (d OR e OR f), was used to search in the title and abstract. The identification step resulted in a total of 1535 articles (IEEEX: 55; PubMed: 160; Scopus: 568; Web of Science: 752). After the removal of the duplicates, 859 articles remained for further screening.

B. *Selection Criteria*

The selection of the articles went through three stages. In the first stage, the title and abstract text were screened to identify unrelated articles. The reasons for rejecting articles included the document being:

(1) on non-human studies.
(2) on non-upper-limb studies (organs, lower limbs etc.).
(3) on the rehabilitation of motor functions rather than spasticity-related syndromes.
(4) on the efficacy of therapy approaches for spasticity.
(5) merely on manual clinical scales, not involving any other instruments or robotic systems.

(6) merely on the design and development of robotic devices, not related to spasticity assessment functionality.

After the first stage, there were 124 research articles and 15 reviews were retrieved for full-text screening. Among them, 33 research articles and 6 reviews were further excluded as they did not match the above selection criteria, or their research results were outside the scope of this review. We also added 8 research articles and 5 reviews that were identified from the citation search to the included papers. Finally, our review included 99 articles and 14 relevant reviews in total.

Among the selected papers, we found that only a relatively small number of papers targeted hand spasticity assessment, much less RAHSA (see Fig. 2 and 3). Considering the relevance and potential transferability of assessment techniques of upper limb spasticity to hand-related studies, we conducted a two-stage literature review to fill the gap between pathology-based spasticity measures and robotics-based rehabilitation techniques. The first stage was reviewing and evaluating existent instrumented spasticity assessment methods for upper extremities in terms of spasticity pathology and clinical requirements. With the understanding of the state-of-art in general spasticity assessment approaches, we then concentrated on studies about RAHSA in the second stage, to show the research gaps between the hand-related studies and other studies, and potential directions for future research inspired by existing achievements.

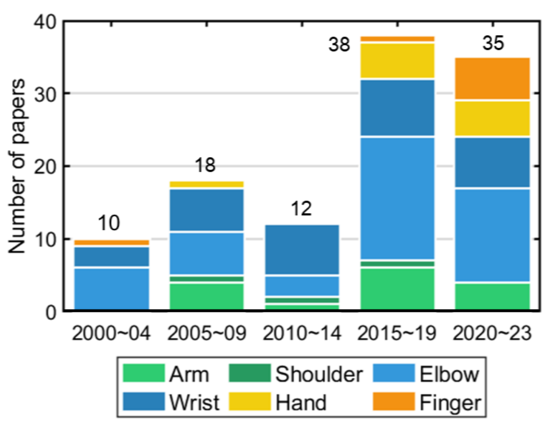


Fig. 2. The number of research articles on instrumented spasticity assessment of different upper extremity limbs from 2000 to 2023.

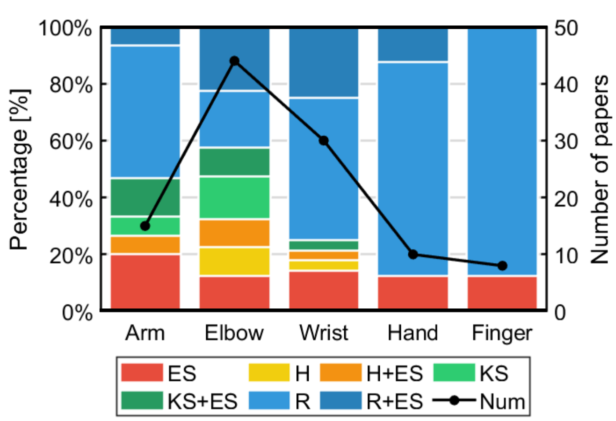


Fig. 3. Instruments used for assessing spasticity in different limbs. The stacked histogram shows the percentage of used instruments. The line is the total number of papers of different limbs. ES, electrophysiological sensors; H, handheld instrument; KS, kinetic sensors; R, robotic device.

TABLE I
DEFINITION OF THE INSTRUMENT CATEGORIES

Abbr.	Denotations	Definitions
ES	Electrophysiological sensors	Surface electromyography and mechanomyography
H	Handheld instrument	Dynamometer, electronic or optical goniometer, myometer, myotonometer and other manual measurement tools
KS	Kinetic sensors	Inertial measurement unit, motion capture system, force transducer, load cell and gyroscope
R	Robotic device	Soft robot, exoskeleton, end-effector robot and robotic arm

C. *Statistics of the Past-decade Literature*

We divided the studied limbs in the 99 research articles into six categories: whole arm (N=15, 15%), shoulder (N=3, 3%), elbow (N=44, 44%), wrist (N=30, 30%), hand function (N=10, 10%) and finger muscle (N=8, 8%). Some studies involved multiple limbs so the sum of the numbers (N=110) exceeds 99. The distribution of these studies over time is illustrated in Fig. 2. The number of studies on instrumented spasticity assessment of upper extremities has risen significantly, from 10 in 2000 to 35 in 2023, indicating a notable upward trend. The slight decrease in the article count from 38 in the period '2015-2019' to 35 in '2020-2023' can be attributed to the latter period being shorter or COVID-19 pandemic [23]. Studies on hands and fingers have gradually taken up a greater proportion, rising from 0 to 31% between 2010 and 2023. The research on spasticity assessment of elbows and wrists always occupied the largest proportion in the last decade (23%-60% for elbow and 20%-58% for wrist). This is likely due to the relatively simpler symptoms of elbow and wrist spasticity compared to those of hand spasticity, so the spasticity of these two joints is easier to monitor and analyse. For example, an elbow with spasticity normally has a clear angle threshold of stretch reflex, which is an effective measure of spasticity, while such an angle threshold cannot be found on spastic hands [24, 25]. Apart from that, the higher incidence rates of elbow and wrist spasticity suggest that they may have greater clinical importance than other limbs, probably attracting more research attention [26].

We summarised the types of instruments used in the covered studies, as shown in Table I and Fig. 3. The studies about shoulders were excluded due to the scant number of papers (one paper for each year group in Fig. 2). ES was applied to assess all five categories of upper limbs and was often used in conjunction with other instruments. Interestingly, although H and KS were used in the study of arm, elbow and wrist, they did not appear in the study on hand. This probably implies that hand spasticity assessment is more demanding for instrument functions, hence the introduction of robotic devices becomes more significant.

III. COMMON APPROACHES OF INSTRUMENTED ASSESSMENT FOR UPPER EXTREMITY SPASTICITY

The SPASM consortium completed several comprehensive literature reviews on clinical scales, biomechanical approaches, and neurophysiological approaches to examine the development and shortcomings of prior spasticity assessment approaches in 2005 [27-29]. Many of these approaches have been combined with robotic technologies to advance assessment performance [4, 21]. We combined several published reviews with the papers covered in our literature review, making Table II to summarise the prior research on instrumented upper extremity spasticity assessment [4, 16-21]. The categorisation in Table II follows the classification approach in the prior typical reviews on spasticity assessment [16-20, 27-29]. All selected articles were categorised accordingly, as the 'References' column of Table II.

A. Clinical Scales

A robot is mostly meant to replicate what clinicians do for spasticity assessment; therefore, adopting the most effective assessment procedure and having a good implementation of that is an efficacious approach for robotic assessment [30-32]. In most clinical settings, clinicians rely on manual clinical scales to assess spasticity conditions. Clinical scales are typically composed of a set of procedures and measures for performing assessments manually, along with criteria for grading measurement results [27]. However, manual operation introduces subjective biases and measurement errors and thus needs the help of robotic devices [33, 34].

TABLE II
SUMMARY OF INSTRUMENTED ASSESSMENT APPROACHES OF UPPER EXTREMITY SPASTICITY

Category	Measures	References
Clinical scale [27]	Instrumented MAS	[30, 31, 35-38]
	Instrumented MTS	[32, 39, 40]
	Instrumented Brunnstrom	[41]
Biomechanical [28]	Range of motion (ROM)	[42-49]
	Catch of angle (CA)	[42, 46, 48, 50-52]
	Resistance force	[50, 53-69]
	Force components	[69-78]
	Impedance (inertia, stiffness and viscosity)	[43-45, 48, 54, 56, 60, 63, 67, 78-89]
	Voluntary motion (velocity, acceleration, smoothness and accuracy)	[43, 60, 90-96]
	Voluntary force (gripping and contraction forces)	[43, 44, 46, 47, 78, 97-102]
	Tissue mechanical property	[103, 104]
Neurophysiological [29]	Hoffmann reflex	[79, 105-107]
	Stretch reflex	[24, 25, 50, 55, 57, 58, 63, 68, 79, 82, 108-112]
	EMG recordings during voluntary motion	[63, 97, 98, 101, 102, 113-116]
	Transcranial magnetic stimulation	[117]
	Muscle fibre conduction velocity	[118]
	Mechanomyography	[119]
Medical imaging	Ultrasound	[20]
	Near infrared light	[19]
	Magnetic resonance imaging (MRI)	[74]

The most widely used clinical scale is the Modified Ashworth Scale (MAS) [17, 18]. It grades the severity of spasticity based on the resistance to passive motion of the assessed limb. The MAS does not consider the velocity dependency of the resistance, as well as fails to discriminate between neural components caused by abnormal muscle reflexes (spasticity) and non-neural components caused by pathological changes in soft tissue (contracture) [120, 121]. To overcome the defects of the MAS, the Modified Tardieu Scale (MTS) was proposed, which examines the resistance at both fast and slow velocities [122]. It can differentiate between contracture and spasticity severity more effectively than the MAS [121]. However, the MTS does not fundamentally solve the problems of subjectivity in judgment, ambiguous words in descriptions, errors in measurement, and variability in stretch velocity [123].

Although these clinical scales have limitations, they are still widely used in current research and clinical environments because of their familiarity, simplicity, and low cost [16, 18]. In order to compensate for the limitations of manual clinical scales, some prior research designed instruments to assist the measurement of clinical scales [30-32, 35-41]. Measurement systems based on inertial sensors were suggested to replace the goniometer in the MTS [39]. Inertial sensors are light and small, so they are easy to mount on limbs to precisely track joint angles [36, 124]. The inertial-sensor measurement system can effectively increase the test-retest and inter-rater reliability of the MTS [39]. The functionality of visual biofeedback was introduced into the inertial-sensor system as well, which can provide consistent passive stretch velocity [40].

Some hand rehabilitation robots are capable of automatically performing the MAS and MTS on hands. Their mechanical structures actuated by motors can flex and extend the fingers at a certain velocity, while embedded sensors can register the force and angle data [31, 32]. Furthermore, in the recent five years, some researchers managed to predict the grade of clinical scales based on machine learning classification or regression algorithms [35-38]. Kim et al. [36] developed a data-driven model to predict MAS scores of elbow spasticity, where the input attributes of the model were the kinematic features registered by a wearable inertial measurement unit during passive extension and flexion. Ye et al. [38] proposed a backpropagation neural network model, mapping the mathematical features of surface Electromyogram (sEMG) signals from elbow and wrist muscles to MAS scores. The scores predicted by the model have a good to excellent correlation with the manual MAS.

B. Biomechanical Approaches

Biomechanical approaches for spasticity assessment use the kinematic and dynamic data of limb movement to evaluate the severity of spasticity. They are normally assisted by measurement tools or instruments to record the displacement and force information [28, 125]. With the introduction of robotic devices highly integrating motorized actuators, more advanced assessment approaches based on biomechanical models have been invented [70, 83, 86].

1) Displacement

The most accessible biomechanical measures for a robotic device are the kinematic parameters of limb motion, e.g., range of movement (ROM), catch angle (CA), and movement profile [42-52]. ROM is measured by exerting a slow and strong enough stretch to extend or flex a joint as much as possible without pain or damage to soft tissues. The slow velocity is to minimise the influence of stretch reflexes. By excluding the influence of neural reflexes, ROM can assess the abnormality of soft tissues related to spasticity, such as contracture [45, 47]. CA is often used in combination with ROM. CA is the onset angle where an obvious rise of resistance force appears during a fast passive movement. It is caused by stretch reflexes, so it is a commonly used sign of spasticity [50, 52].

The spatiotemporal characteristics of voluntary movement during certain robot-guided tasks are also common measures for spasticity. These include variability of angle, velocity and acceleration profiles, velocity smoothness, and target position matching [43, 60, 90-96]. They show the active motor function under the influence of spasticity, potentially connecting spasticity assessment to activities of daily living (ADL).

2) Force

Resistance force is another category of biomechanical measures for upper extremity spasticity [50, 53-69]. The main features of the resistance force of spasticity are the velocity dependence and the mix of the neural component caused by spasticity and the non-neural component caused by contracture [15, 50, 70]. As robotic devices can provide steady isokinetic motion, they can capture the features of the resistance force at a specific velocity more easily and reliably than manual assessment [50, 58, 62, 65, 68].

Although the sensors on robotic devices can register the resistance force, the abnormality found in the force data cannot be exclusively explained by spasticity, because contracture also contributes to the resistance [126, 127]. As a result, biomechanical measurement models of resistance force were implemented on robotic devices in some research to separate the neural and non-neural components [68, 70]. The NeuroFlexor is a typical robotic device for the model-based measure. It is capable of evaluating finger and wrist spasticity by resolving the resistance force against passive movement into inertia, elasticity, viscosity, and neural components. It has been proven that the measurement of the device is significantly correlated with the MAS [69, 78].

Similar to the displacement measures of voluntary movement, the force of voluntary muscle contraction was also studied to establish the relationship between spasticity and motor function [43, 44, 46, 47, 78, 97-102].

3) Impedance

Impedance is referred to the resistance of a system to an external perturbation in physics, which can describe the response property of the human musculoskeletal system to external perturbation [128]. The main sign of limb spasticity is the change of joint mechanical property under the influence of external stretches, so that impedance can be used to evaluate spasticity conditions [43-45, 48, 54, 56, 60, 63, 67, 78-89]. Impedance can be estimated through a state perturbation while observing the resulting force change or, conversely, by a force perturbation while observing the resulting state change [128]. A valid impedance measurement needs precise motion control and accurate force-sensing information, so it is normally conducted using robotic devices.

In some research, the passive impedance property of limbs was simplified into a second-order linear system. The estimated parameters of the impedance model include all or part of elasticity (stiffness), viscosity (damping) and inertia (mass) [63, 80, 88, 89]. However, some other research has proved that this linear model fails to describe the complex mechanism of neuromuscular control or the mechanical property at joint movement boundaries, so more sophisticated models have been developed to overcome these problems, including modified viscoelastic model, finite element models and non-linear models [83, 86, 87, 128]. Apart from the model, the range, speed, and duration of the perturbation should be designed carefully as well to make the estimated perturbation parameters meaningful from the aspect of pathophysiology [128]. Although many previous studies have shown that impedance is strongly related to spasticity severity, the lack of pathophysiological explanations for impedance values, as well as limitations in measurement reliability, make it difficult to apply this approach in a clinical setting [57, 86, 88].

C. Neurophysiological Approaches

Despite the fact that the definition of spasticity has always been debated, the consensus about spasticity is that it is abnormal muscle activity caused by neural deficits [7]. The most popular measurement technique of muscle activity for spasticity is sEMG, which illustrates the electrical signals of muscle excitation prior to the mechanical activity of skeletal muscles [29]. The sEMG signals that can be measured for spasticity assessment include the neural reflexes induced by electrical stimuli, mechanical stimuli, and passive movements [29, 129]. Although the mechanisms of these reflexes differ, the measurement parameters are similar, including the latency and amplitude of reflexes and the ratio between them [29].

Passive movement of limb joints at a high enough speed can elicit stretch reflexes. Stretch-reflex assessment approaches do not need special electrical stimulation devices and do not have constraints on limbs, so they are easier and more suitable to be implemented on robotic devices than other reflexes [25, 50, 63, 79, 88]. Some studies combined biomechanical and neurophysiological techniques, proposing the measurement of the Tonic Stretch Reflex Threshold (TSRT) as an indication of spasticity levels [24, 130]. TSRT of a limb joint refers to the joint angle where abnormal muscle resistance is observed, despite the joint velocity being zero. It is obtained from the spasticity onsets (spatial thresholds) at multiple velocities of the tested limb, so this approach needs both EMG and kinematics data during passive movements [131]. Although this assessment approach does not show obvious superiority to clinical scales in terms of reliability, its responsiveness to spasticity change is much better [24, 132].

Neurophysiological approaches quantify spasticity via motoneuron activity, so they are explainable from the aspect of the pathophysiology of spasticity. As a result, they were used as a ‘gold standard’ for evaluating other approaches [57, 105]. Nevertheless, the complex setup process and limited robustness of EMG techniques hinder their widespread adoption in clinical settings [133]. The EMG measurement performance is likely to be influenced by the placement of electrodes, tissue structures, and interferences from environments, resulting in high variability from session to session. Also, due to the natural variability of muscular signals in the population, it is difficult to compare EMG parameters between subjects [29, 133].

D. Other Approaches

Medical imaging is becoming a new research focus for spasticity assessment. Researchers examine the anatomical, mechanical or physiological properties of spastic muscles or related brain areas [17-20]. Several previous studies have demonstrated the validity and reliability of these approaches to assess spasticity and monitor therapy efficacy, but they all need specific equipment that are often costly and bulky, so there has been no attempt so far to integrate them into robotic systems for spasticity assessment [19, 20].

IV. ROBOT-ASSISTED HAND SPASTICITY ASSESSMENT

According to the review above, some upper limb spasticity assessment approaches have been attempted in combination with robotic devices, and some findings have been productised [24, 69]. Unlike the elbow and wrist, RAHSA did not see substantial progress until the last decade. We summarised the 12 retrieved studies (spanning 13 articles) on RAHSA in Table III and analysed them in terms of used robots, assessed hand joints, assessment approaches, and experimental evidence.

A. Hand Robots for RAHSA

A wide range of hand rehabilitation robots has been developed in the last two decades, but robotic devices applicable to RAHSA are rare [6, 32, 96]. The robotic devices for RAHSA mainly include end-effector robots and exoskeletons, which can be further divided into fixed-arm end-effectors, free-arm end-effectors, rigid exoskeletons and soft exoskeletons, as shown in Fig. 4.

End-effector robots can train or test typical hand functions, such as gripping, twisting, and pinching. They are usually mounted on a platform to avoid the additional load on spastic limbs [25, 31, 49, 61, 67, 74, 100]. According to the constraints of arms, they are categorised into the two categories of fixed-arm and free-arm end-effectors.

Fixed-arm end-effector robots for RAHSA typically restrict most degree of freedom (DOF) of arms and merely allow the motion of finger joints [25, 31, 49, 74]. These robots consist of multiple linkages to which the user’s lower arm, palm, and fingers are attached separately. The evaluated finger joint aligns coaxially or parallel to the axis of the actuated linkage joint [25, 31, 49, 74]. Differently, free-arm end-effector robots preserve more DOF of arms and hands. These robotic devices usually feature a handle that can be grasped or pinched by the tested hand. The handle can be rotated or flattened with the hand, either actively or passively [61, 67, 100]. Since the rest joints of the arm are not fixed, users can flexibly move their proximal arm joints while using. Research based on this kind of robot is normally concerned more with the impacts of spasticity on hand motor functions [61, 67, 100].

The design of a hand exoskeleton is characterised by the structure conforming to the anatomy of hands. The highly adaptable construction of hand exoskeletons allows them to apply delicate motion to individual fingers or even individual finger joints. Existing hand exoskeletons for assessing spasticity can be generally categorised into rigid and soft exoskeletons [32, 38, 41, 86, 87, 96].

For a rigid exoskeleton, the mechanical parts are made of hard metals or plastics. The mechanical structure is attached to finger segments, and the rotational axes of the joints corresponding to the DOFs are parallel to the axial rotation of the anatomical joints. In order to fit into the natural musculoskeletal structure of hands and acquire information about multiple joints, rigid exoskeletons are commonly equipped with more complex actuation and sensing systems than end-effector robots considered above; thus rigid exoskeletons usually have a higher costs and lower robustness [32, 38]. With fewer or no rigid structures, soft exoskeletons are more lightweight and compact on the hand. The majority of soft exoskeletons are gloves with soft actuators and elastic components to transmit forces on the fingers [41, 86, 87, 96].

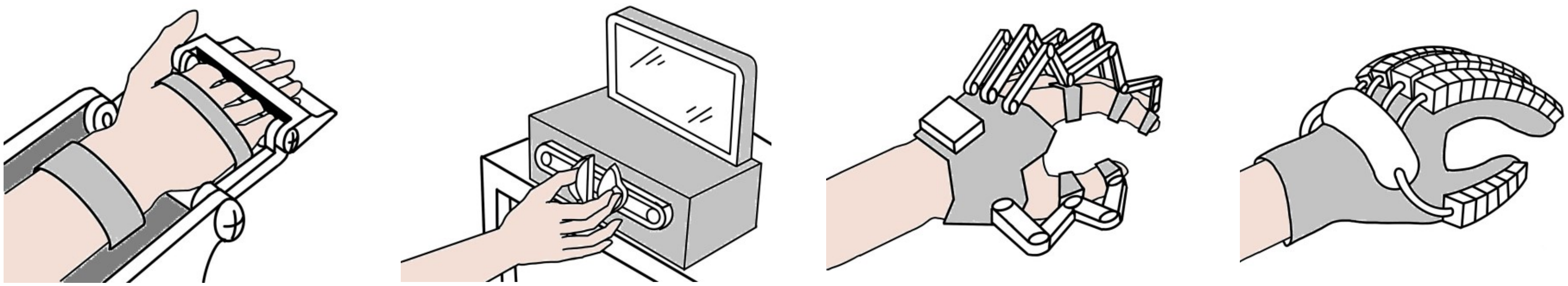
The mechanics of these hand robots determine which hand joints they can assess for spasticity, whereas the sensing system determines the possible types of spasticity assessment that can be realized.

B. Involved Hand Joints of RAHSA

In current clinical environments, physiotherapists typically examine each finger joint individually to assess hand spasticity [140, 141]. Based on this approach, an intuitive goal for RAHSA is to assess all joints separately to get as complete a picture of hand status as possible. However, this objective has not yet been realised well in existing studies on RAHSA.

The majority of studies (N=7) on RAHSA have evaluated spasticity conditions by examining biomechanical properties common across multiple finger joints. Kamper and Plantin et al. investigated the collective mechanical resistance of the metacarpophalangeal (MCP) joints of the second to fifth fingers during stretching in post-stroke patients [25, 74]. Some other papers proposed the spasticity-related characteristics of resistance force exhibited across an entire finger [31, 32, 49, 86, 87]. The hand robots used in these studies were unable to exert independent motion and sensing at individual joints. Only one study attempted to collect kinetic information for each joint separately, but the employed hand exoskeleton was limited to application solely on an index finger [32].

Furthermore, in some studies, the hand robots utilised are unable to passively stretch fingers, especially free-arm end-effectors. As a result, these studies focused on spasticity-related features of a whole hand and its motor function during active finger movements, e.g., gripping [38, 41, 61, 67, 96, 100].



a) b) c) d)

Fig. 4. Categories of RAHSA robotic devices: a) fixed-arm end-effector; b) free-arm end-effector; c) rigid exoskeleton; d) soft exoskeleton.

TABLE III
STUDIES ON ROBOT-ASSISTED ASSESSMENT FUNCTIONALITIES FOR HAND SPASTICITY FROM 2000 TO 2023

Robotic devices	Other instruments	Involved joints	Protocols	Instrumented measures	Experimental evidences	Subjects	Ref.
Fixed-arm end-effector	sEMG	MCP joint of digit 2 to 5	Passive stretches	Resistance force	Discrimination: visually distinguish between higher and lower than MAS 2.	P 13 H 2	[25]
	-	Digit 1 to 5	Passive stretches	ROM Resistance force	Criterion validity: excellent correlation with MAS (ICC=1.00) and good correlation with TS (ICC=0.79, p=0.02).	P 10 H 0	[31]
	-	Digit 1 and 3	Passive stretches	ROM, resistance force	-	P 18 H 4	[49]
	MRI	MCP joint of digit 2 to 5	Passive stretches	MRI image features Force components	Discrimination: numerically discriminate no, moderate and severe spasticity; Criterion validity: fair correlation with MAS (R=0.57, p<0.0001) and good to fair correlation with wCST-LL (R=0.49-0.61, p<0.0001).	P 61 H 0	[74]
Free-arm end-effector	-	Hand	Ramp-and-hold perturbation	Resistance force	Criterion validity: no correlation with MAS	P 5 H 5	[61]
	-	Hand	Ramp-and-hold perturbation	Resistance force Impedance	Construct validity: identify spring stiffness with a RMSPE of 3.8% to 11.3%; Criterion validity: no correlation with MAS; Discrimination: distinguish between stroke and unimpaired groups (p<0.001).	P 6 H 10	[67]
	-	Hand	Reaching and pulling tasks	Voluntary motion	Discrimination: visually distinguish between stroke and normal subjects.	P 6 H 27	[100]
Rigid exoskeleton	sEMG	Hand	Reaching tasks	sEMG during voluntary motion	Criterion validity: significant correlation with MAS (R=0.91, p<0.001); Responsiveness: significant difference between the pre- and post- intervention sessions (paired t-test, p<0.001).	P 29 H 0	[38]
	-	MCP, PIP, and DIP joints of digit 2	Passive stretches	ROM Resistance force	-	P 0 H 1	[32]
Soft exoskeleton	-	Digit 2 to 4	Stacking tasks	ROM Resistance force	Discrimination: classify the subjects at Brunnstrom stages 3 and 4 (sensitivity is 96.6%, specificity is 56.5%, and misclassification rate is 21.0%).	P 10 H 0	[41]
	Camera	Digit 2	Passive stretches	Impedance	Discrimination: numerically discriminate between MAS 3 and MAS 0-1. Criterion validity: 0.004-0.021Nm/rad difference from the standard stiffness measurement	P 4 H 4	[86, 87]
	Pressure ball	Hand	Cone stacking Voluntary motion Ball squeezing	Voluntary motion	Discrimination: distinguish between stroke patients with spasticity and healthy subjects (p<0.05).	P 7 H 7	[96]

MCP, metacarpophalangeal; PIP, proximal interphalangeal; DIP, distal interphalangeal; Digit 1 to 5, thumb, index finger, middle finger, ring finger, and little finger; ROM, range of motion; MAS, Modified Ashworth Scale; TS, Tardieu Scale; wCST-LL, weighted corticospinal tract lesion load; P, patients; H, healthy controls

C. Biomechanical Measures of RAHSA

With position and force sensors, most RAHSA robots are capable of performing biomechanical assessments. Researchers usually first measure the natural ROM under passive movement to determine the appropriate range of finger extension and flexion to be applied by the robot [31, 32]. Moreover, Kim et al. proposed the measure of functional ROM, which corresponds to the difference in finger joint angles between the release and grab moments when subjects perform stacking tasks with mirroring gloves [41].

In order to study the finger joint resistance force of spastic patients, researchers apply two types of movements to the finger joint: short perturbations or extension/flexion across the entire ROM. Ranzani et al. studied the finger resistance force against fast and slow perturbations during pinching tasks [61, 67]. As they merely concerned the first 100 ms after the perturbation onset, this kind of resistance force is relevant to reflex reactions and excludes the confound of voluntary control [61, 67]. Differently, some studies stretch finger joints over the whole ROM, so the registered resistance force can indicate a complete picture of spastic muscles [25, 74].

In the impedance measures for RAHSA, stiffness is the most commonly estimated parameter. Ranzani et al. estimated the endpoint stiffness during pinching tasks to assess hand tone levels. This stiffness incorporates the stiffness of the thumb and other digits [67]. In contrast, Shi et al. and Heung et al. examined the proximal interphalangeal joint and MCP joint stiffness of the index finger separately [86, 87].

D. Neurophysiological Measures of RAHSA

We identified only two studies on RAHSA that used sEMG [25, 38]. Kamper et al. recorded the sEMG of extrinsic muscles over passive stretches of the MCP joints. The EMG signals were analysed to identify the activation of the stretch reflex in flexors, as well as the anomalous increase in extensor muscle activity. They found that reflex responses in spastic finger flexors appear from the starting of passive stretches, and stretching finger flexors may evoke shortening reflexes in the extensors [25]. In another paper employing sEMG, Ye et al. proposed a backpropagation neural network model, mapping the mathematical features of EMG signals from elbow and wrist muscles to MAS scores of elbow, wrist, and finger. The EMG features used to train the neural network model were extracted from arm EMG signals during reaching tasks [38].

Neurophysiological information about spasticity can be also collected through MRI. Plantin et al. utilised MRI to scan the corticospinal tract lesion load of post-stroke patients [74]. The NeuroFlexor device was also used in this study to register the neurological components in the resistance force. Their experiment results implied that the lesion load of corticospinal tract is related to hand spasticity but the insight into the relationship between them needs further research.

E. Experimental Evidence of RAHSA

Regardless of the type of measures, a new RAHSA approach requires sufficient experimental evidence to prove its clinical validity and practicality [4, 15]. Among the 12 surveyed studies, half (N=6) recruited ten or more patients, with the study by Plantin et al. involving the largest number of 61 patients [74]. Additionally, half of the studies (N=6) recruited healthy subjects as controls. Utilising the data collected from these subjects, psychometrics were further computed to evaluate the clinical performance of these RAHSA approaches.

As a basic psychometric measure, reliability includes the inter- and intra-rater reliability and test-retest reliability, reflecting the agreement of assessment results among independent assessors, the repeatability of assessment results by a single assessor, and the consistency across multiple tests, respectively [78, 134]. In the investigated studies on RAHSA, none of them specifically reported psychometric reliability. Instead, six (50%) studies demonstrated the measurement consistency through the variance and significance level of collected data [38, 61, 67, 74, 86, 87].

Discrimination between healthy and spastic patients is a preliminary demonstration of the validity of a spasticity assessment approach. There are seven studies (58%) claiming that their assessment approaches can distinguish between healthy subjects and stroke patients with spasticity. Among them, two studies substantiated the claim with statistical tests ($p<0.001$ in [67] and $p<0.05$ in [96]), while one study provided a misclassification rate of 21.0% [41]. The remaining four studies drew this conclusion through visual plots or numerical comparisons [25, 74, 86, 87, 100].

Criterion validity is an estimate of how much a measure agrees with a gold standard. The most common gold standard for RAHSA is MAS, but this assumption is controversial because MAS is reported to be unreliable in some studies [120, 121, 123]. While five papers addressed the correlation between the proposed RAHSA and MAS [31, 38, 61, 67, 74], two of them did not identify a significant correlation [61, 67]. Specifically, the assessment approach in [31] demonstrated an excellent correlation with MAS (ICC=1.00).

The approaches based on theoretical hypotheses or models should prove the construct validity, which shows how well the approach measures the desired construct [55, 75]. In the study involving impedance estimation, construct validity was tested by measuring the stiffness of standard springs [67].

Responsiveness evaluates the sensitivity and resolution of an approach to the changes in spasticity conditions following treatment. Only one study conducted a statistical analysis of responsiveness, revealing significant differences in the assessment results of their RAHSA between pre- and post-intervention sessions (paired t-test, $p<0.001$) [38].

V. Discussion

As mentioned in Section III, there is no widely-accepted new approach for upper extremity spasticity replacing clinical scales, as no such new approach has yet proven to be a valid, reliable, and practical alternative, much less the approaches for RAHSA. To tackle these issues, future research on RAHSA must overcome the challenges of assessment approaches and robotic assessment devices.

A. Challenges of Assessment Approaches

Medical image is an effective assessment of hand spasticity, which can evaluate the related cortex lesion and the physical properties of soft tissue during both active and passive movements. This approach requires specialised imaging equipment so it would be costly and difficult to integrate medical imaging with rehabilitation robots [18, 20].

It is much easier for robotic systems to gather kinematic and kinetic data of fingers than elastography, but the kinematic and kinetic data need to be further processed according to an evaluation model (e.g. resistance model and impedance model) to separate the neural and non-neural components. A resistance model for finger passive movements, similar to the NeuroFlexor wrist-resistance model, may be useful to make breakthroughs in the biomechanical assessment of hand spasticity [69-78]. An impedance model can provide an in-depth analysis of the biomechanical data as well, but the perturbations used to measure the impedance may introduce inseparable reflex confounders.

For assessing the neurological factors of hand spasticity, the stretch reflex approach is more suitable to be implemented on robotic devices than electrical stimulation reflexes. The electrical stimulation needs additional devices, so it could significantly increase deployment time and assessment instability [135]. The stretch reflex is triggered by passive movement at a specific speed, which is a basic function of hand rehabilitation robots. Some hand exoskeletons can stretch individual fingers and finger joints, making them suitable for assisting in the stretch reflex assessment of hands [136, 137]. Some previous research on the stretch reflex of finger MCP joint found that there is no clear angular reflex threshold like the situation at elbows, indicating that the application of some stretch reflex approach on hands, e.g. TSRT, would be more challenging than applying on other limbs [25].

With regards to the psychometrics of RAHSA, the clinical trials for RAHSA are still limited, compared to studies on other body limbs [4]. The complete and strong clinical evidence of a newly-proposed RAHSA should include the test of reliability, construct validity, criterion validity, and responsiveness, like the previous research on NeuroFlexor [69-73, 75-77]. Additionally, the necessary psychometrics include minimal detectable change (MDC) and minimally important clinical difference (MCID) [15, 27, 34, 138]. MDC refers to the minimal difference between measurements that indicate a biologically significant change. This measure can determine whether a seemingly positive change in spasticity outcome measurements is a real improvement rather than a statistical deviation [24]. MCID corresponds to the minimal change of the measurement that is meaningful for patients.

Last but not least, the relationship between hand spasticity and motor function recovery remains unclear and therefore needs further research. Although some studies made attempts to correlate the measures of active motion with spasticity levels, their results did not show a reliable correlation between spasticity severity and motor function recovery [74, 100].

B. Challenges of Robotic Systems

Spasticity may occur in different hand muscles. The combination and interaction between spastic muscles may result in abnormal reflexes or stiffness in multiple joints [2, 14, 139]. A hand rehabilitation robot with the functionality to assess individual finger joints not only provides much information to cope with the complex multi-articular musculature of fingers but is also in line with the current clinical assessment practice [140, 141]. However, most existing robotic devices for RAHSA merely have the functionality of measuring the collective spasticity conditions of multiple joints or whole hands rather than individual finger joints. This could be because the capability of actuation and sensing for each finger joint may increase the complexity of the robotic device, implying a larger, bulkier, and heavier device, and a higher cost [136, 137].

Additionally, our previous analysis has pointed out that one of the limitations of pure biomechanical measures is not taking the neurological factors into account. A promising direction for RAHSA is combining the approach for neurological information with the approach for non-neurological information [15]. This means that the hand exoskeleton must be capable of not only moving the finger joints according to targeted profiles but also robustly recording related kinematic and dynamic data, as well as collecting biological information, such as EMG signals. Richer and multi-modality spasticity-related information will also provide the basis for the development of data-driven assessment algorithms [37, 38].

To balance the assessment functionality and system complexity, some design ideas from prior studies could be exploited. Firstly, the mechanical structure of the robotic system could be simplified according to the physiological features of hands. For example, the MCP joints of four digits are controlled by the same extrinsic and intrinsic muscle groups, so they can be moved as a combined unit with a single actuated DOF [25, 32]. Secondly, introducing an external measurement system could make the sensing system simpler. It is a good example that a hand gesture system based on a camera could replace angle sensors of multiple finger joints [86, 87]. Thirdly, taking inspiration from the evaluation principles of NeuroFlexor, it is feasible to establish biomechanical models that delineate the neural component of finger joint resistance caused by the stretch reflex. This approach only needs sEMG during the functional development and validation phases, eliminating the necessity to integrate sEMG electrodes into the robotic device [68, 70, 72].

VI. Conclusion

In this study, we review the instrumented assessment approaches for upper extremity spasticity that have emerged over the last two decades. Novel clinical scales, biomechanical and neurophysiological approaches, and medical imaging techniques all exhibit limitations, hindering their widespread application in clinical environments. Even though the introduction of robotic systems has achieved multidimensional and more reliable measurement than manual assessment, in the clinical settings, the manual MAS assessment remains the predominant method for evaluating spasticity.

The studies on RAHSA are less numerous than those on instrumented spasticity assessment of wrist and elbow. Some instrumented measures of spasticity have been implemented on hand robots to facilitate RAHSA, but these new approaches require more comprehensive and convincing clinical evidence to break through the barriers to clinical application. More research should be conducted on the combination of neurophysiological and biomechanical measurements, as well as on developing novel robotic systems for hand spasticity assessment.

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