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Rehabilitative and assistive wearable mechatronic upper-limb devices: A review

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Abstract
Recently, there has been a trend toward assistive mechatronic devices that are wearable. These devices provide the ability to assist without tethering the user to a specific location. However, there are characteristics of these devices that are limiting their ability to perform motion tasks and the adoption rate of these devices into clinical settings. The objective of this research is to perform a review of the existing wearable assistive devices that are used to assist with musculoskeletal and neurological disorders affecting the upper limb. A review of the existing literature was conducted on devices that are wearable, assistive, and mechatronic, and that provide motion assistance to the upper limb. Five areas were examined, including sensors, actuators, control techniques, computer systems, and intended applications. Fifty-three devices were reviewed that either assist with musculoskeletal disorders or suppress tremor. The general trends found in this review show a lack of requirements, device details, and standardization of reporting and evaluation. Two areas to accelerate the evolution of these devices were identified, including the standardization of research, clinical, and engineering details, and the promotion of multidisciplinary culture. Adoption of these devices into their intended application domains relies on the continued efforts of the community.

Introduction

Technological research and increasing demands for motion assistance are driving societies towards a world in which this demand can be met through assistive mechatronic devices. According to the Global Burden of Disease study in 2016, approximately 2.5 billion and 1.2 billion people suffer from neurological disorders (NDs) and musculoskeletal disorders (MSDs), respectively.[1] Many of these disorders will require some form of rehabilitation, motion training, or motion assistance for at least a portion of time after the onset of the disorders. For other progressive disorders, the dependence on assistance with activities of daily living (ADLs) will increase over time. Studies of the economic burden of MSDs in many countries have shown yearly costs of approximately $33.5 billion in Canada,[2] $231 billion in the USA,[3] $1.3 billion in Chile,[4] and $15.6 billion in Sweden.[5] These burdens

will continue to grow as the population grows and the proportion of the population needing motion assistance increases. Meeting this demand with traditional intervention strategies may become unfeasible as the demand continues to grow at a faster pace than available resources.

The potential for assistive upper-limb devices to provide improved quality of life to humans has been

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expanding the number of research endeavors in this field over the last few decades. This increase in research comes as the earlier devices have been shown to be effective tools for assistance in clinical trials.[6,7] The number of devices entering this research community has generated many reviews. In 2011, Gopura et al. provide a brief examination of upper-limb exoskeletons, categorized by actuation type.[8] Lo and Xie investigated existing upper-limb exoskeleton systems with a summarization of the key challenges faced by these systems in 2012.[9] In 2014, Maciejasz et al. conducted an extensive review of upper-limb devices, which features over 120 rehabilitation systems.[10] This review examined the combined contributions of portable and non-portable devices and revealed the shift toward wearable devices, although many of the systems are non-portable. Furthermore, this study is missing a detailed discussion of the sensing and computer systems, which are critical components of mechatronic systems. The review presented here aims to complement the one conducted by Maciejasz et al. by focusing on portable devices and including additional areas of review.

Increasing the wearability and portability comes from improvements, such as weight, volume and power reduction, increasing accuracy, optimizing computational resources, and estimating uncertainties. These improvements require further research efforts in sensor, actuator, control, and computer systems. The objective of this review is to explore the existing research contributions in the area of wearable assistive mechatronic devices for the upper limb. First, an overview of the state-of-the-art of these devices for the upper limb will be presented. Next, a detailed analysis of five key areas, sensing, actuation, control, computation, and applications, will provide evidence of successes and limitations of existing technologies and methods. Finally, the challenges faced by this research community will be discussed, and future directions identified.

Review criteria and methods

Innovation of wearable assistive mechatronic devices is out-pacing the standardization of terminology of the research areas involved in their development. As a result, terms, such as exoskeleton, robot, manipulator, and mechatronic device are being used interchangeably making it difficult to dissect these fields of engineering. In order to eliminate this confusion, the following definitions of the criteria are proposed, in order to clarify the review and the distinctions between devices. In this review, devices are chosen based on their fulfillment of the following four criteria: wearable, assistive, mechatronic, and for the upper limb. *Wearable* is identified as

the property that the base of a manipulator originates from one or more attachment points on the human body. This distinction is made to exclude exoskeleton- or end-effector-based systems where the base of the manipulator originates from attachment points in the environment, such as the floor or wall, and, therefore, limits the wearability of the system. Furthermore, this definition includes devices that are intended to be wearable, but may not be fully portable due to limitations in their components. *Assistive* implies that the device is able to provide assistance to the user during completion of motion tasks. A distinction made in this review is that assistance is viewed as the generation of forces to either support a desired motion, such as during rehabilitative interventions, or to suppress an undesired motion, such as in tremor suppression. A *mechatronic* device encompasses systems that are comprised of mechanical and electrical components, and has been programmed to automatically complete complex tasks, such as assisting with human motion. The four major components of mechatronic system are the mechanical, electrical and electronic, computer, and control systems. Any devices or systems that fit these criteria and are intended to assist with *upper-limb* motion, including the thoracic spine, cervical spine, shoulder, elbow, wrist, or hand, were candidates for this review.

In this review, the sensing, actuation, control, and computer systems of these devices will be examined to identify the state-of-the-art and challenges facing their future. Sensors and actuators are required to measure and manipulate biological properties of the user. Control systems are needed to ensure proper behavior of the device. Communication and processing of biological, environmental, and device information is facilitated through computer systems. Although all of these sub-systems may not be needed for the devices to be classified as a mechatronic system, these sub-systems have been identified as necessary to provide motion assistance to humans. Since it may not be possible to fully describe the details of all sub-systems in a single manuscript, an article must contain at least brief descriptions of three of the four sub-systems to be included in this review. No specific inclusion criteria were used to narrow the scope of the application domains that are targeted by these devices.

The review was conducted by examining the IEEE Xplore, Google Scholar, ACM Digital Library, Scopus, Inspec, and Compex databases for relevant articles. The databases were searched using various combinations of the keywords: assistive, device, exoskeleton, mechatronic, portable, rehabilitation, robot, tremor, and wearable. The initial search resulted in 90 articles that were considered based on keyword matches, abstract content, and brief review of the

article. The next step involved reviewing each article to determine whether or not it met the review criteria. In order to be included in this review, each study had to include a device that met both the definition criteria and the sub-system detail criteria discussed above. Individual authors were assigned to review a portion of the 90 articles. If an author could not determine whether or not inclusion criteria had been met, all authors would review the article and vote on its inclusion. This process resulted in a total of 64 articles that were found to meet the criteria and be considered as part of this review.

Commercially available devices

To date, only one device fits our review criteria and is commercially available. The MyoPro is a wearable assistive device developed for assistance for individuals suffering from NDs, such as brachial plexus injury or stroke.[11,12] The most recent version of the MyoPro uses electromyography (EMG) sensors to detect muscle activity from both the elbow and forearm flexors and extensors in order to assist with elbow flexion–extension and grasping. The sensing, actuation, control, and computer systems are contained within the device making it fully portable and wireless during operation. Multiple clinical studies using the MyoPro to assist with rehabilitation activities for individuals suffering from stroke conclude that rehabilitation using this device is as effective as traditional manual therapy and improves performance during functional tasks when worn.[11,13–15] The successes of the MyoPro support further inquiry into these technologies and show a promising future for wearable assistive devices.

State-of-the-art: Devices in the literature

The goal of this review is to answer the question: what is the state-of-the-art in wearable assistive mechatronic devices for the upper limb? Besides the MyoPro elbow device, the state of the wearable assistive devices lies within the research realm. A total of 53 wearable assistive mechatronic upper-limb devices have been identified from the literature. The majority of the articles reviewed were motivated by disorders such as stroke, Parkinson's disease, essential tremor, spinal cord injury, arthritis, and post-surgical or post-traumatic nerve damage. However, other disorders mentioned in the literature include cerebral palsy, chronic carpel tunnel syndrome, muscular atrophy, multiple sclerosis, congenital disorders, and osteoarthritis. No wearable assistive devices were found that meet the criteria and assist with thoracic or cervical spine motion. Therefore, these two body segments will not be discussed further.

The complexity of the technology and the human body has caused an expansion of research into these devices over the last decade. In fact, 54% of the articles reviewed were published within the last five years. The multidisciplinary nature of these devices coupled with the immaturity of this field has led to diversity of the technologies used. An overview of the major technologies used in these devices can be found in Table 1. Devices in this table have been categorized by the joints they actuate. Brief details about their supported motions, sensed quantities, actuation systems, control quantities, and application type are listed.

Overall, there are a few trends worth noting about the state-of-the-art. First, the bulk of these devices are wearable, but not fully portable. In many cases, either a portion or all of the actuation system, power supply, or communication and control cables tether these devices to a location. Second, the majority of the devices in this review focus on the motion of a single arm segment (87% of devices) with opening and/or closing of the hand and fingers being the largest focus (51% of devices). Improving the movement of even one segment in the upper limb can translate into a better quality of life for those suffering from the disorders. The single-segment approach to the design of these devices has a higher likelihood of finding solutions and, therefore, getting to market and creating a social benefit. Lastly, it should be noted that few clinical studies have been performed on any of the reviewed devices. The devices are still in development and require vigorous testing to ensure human safety. Therefore, the research areas surrounding wearable assistive technologies have many questions that still need to be answered.

The devices considered for this review have been examined based on the topics of sensing, actuation, control, computation, and applications. The major technologies and techniques from each of these topics are discussed in the following sections.

Sensing

Sensors are a major component within wearable assistive devices, as they are able to detect changes within the device, the manner in which the user interacts with it, or the environment. Sensing can be used to influence the system's behavior, allowing it to respond appropriately to user's needs and fulfill the device's purpose.

In 77% of the devices, biological signals were measured and used towards control of the system. These devices can be further sorted into physiological signals, which are electrically representative signals of internal physiological processes of the human body, and biomechanical signals, which are signals measuring the outwards motion performed by the human body, such as joint position and exerted force. The use of sensor

Table I. An overview of existing wearable assistive mechatronic devices.

Author (Reference)	Supported movements	Sensed quantities	Actuation	Controlled quantities	Type of assistance
Shoulder, elbow, and wrist					
Sugar et al.[16]	Shoulder-F Elbow-F, S Wrist-E	Position, pressure	Pneumatic actuator	Torque	Support
Shoulder and elbow					
Brackbill et al.[17]	Shoulder-FE, AbAd, IE Elbow-FE	Not listed	Electric motor	Position	Support
Lessard et al.[18]	Shoulder-Ab Elbow-FE, PS	Position, heart rate	Electric motor	Torque	Support
Elbow and wrist					
Rocon et al.[19]	Elbow-FE, PS Wrist-FE	Velocity, force	Electric motor	Torque, velocity	Suppression
Ueda et al.[20]	Elbow-FE, PS Wrist-FE, RU	Position, EMG	Pneumatic actuator	Force	Support
Xiao et al.[21]	Elbow-FE, PS Wrist-FE, RU	EEG	Electric motor	Position	Support
Elbow					
Ando et al.[22]	Elbow-FE	EMG	Electric motor	Torque	Suppression
Vaca Benitez et al.[23]	Elbow-FE	EMG, position, torque	Electric motor	Torque	Support
Desplenter et al.[24]	Elbow-FE	EMG	Electric motor	Velocity	Support
Herrnstadt and Menon[25]	Elbow-FE	Position, velocity	Electromagnetic brake	Torque	Suppression
Kim et al.[26]	Elbow-FE	EMG, pressure	Pneumatic actuator	Torque	Support
Kleinjan[27]	Elbow-FE	Position	SMA	Torque	Support
Kyrylova[28]	Elbow-FE	EMG, position	Electric motor	Position, velocity	Support
Looned et al.[29]	Elbow-FE, PS	EEG, position	Electric motor	Torque	Support
Pylatiuk et al.[30]	Elbow-FE	EMG, position, pressure	Hydraulic actuator	Force	Support
Ren et al.[31]	Elbow-FE	Position	Electric motor	Torque	Support
Stein et al.,[11] McBean and Narendran[12]	Elbow-FE	EMG	Electric motor	Position	Support
Tang et al.[32]	Elbow-FE	Position, EMG	Pneumatic actuators	Position	Support
Vanderniepen et al.[33]	Elbow-FE	Not listed	Electric motor	Torque	Support
Wang and Huang[34]	Elbow-FE	Position, EMG	Electric motors	Position	Support
Wrist					
Andrikopoulos et al.[35]	Wrist-FE, RU	Position	Pneumatic actuators	Position	Support
Higuma et al.[36]	Wrist-FE, RU	Not listed	Electric motor	Torque	Support
Kazi et al.[37]	Wrist-FE	Acceleration	Piezoelectric actuator	Acceleration	Suppression
Loureiro et al.[38]	Wrist-FE	Position	MRF actuator	Position	Suppression
Taheri[39]	Wrist-FE, RU	Not listed	Pneumatic actuator	Torque	Suppression
Xiao and Menon[40]	Wrist-FE, RU	EMG, torque	Electric motor	Torque, position	Support
Wrist and hand					
Zhou et al.[41]	Wrist-FE Finger-FE Thumb-FE	Position, velocity	Electric motor	Position	Suppression
Hand					
Al-Fahaam et al.[42]	Fingers/Thumb-FE	Force, position, EMG	Pneumatic actuator	Force	Support
Allotta et al.[43–45]	Fingers-FE	Not listed	Electric motor	Velocity	Support

Table I. Continued

Author (Reference)	Supported movements	Sensed quantities	Actuation	Controlled quantities	Type of assistance
Arata et al.[46]	Fingers-FE	EMG, position	LEA	Force	Support
Aubin et al.[47]	Thumb-FE, AbAd	Position	Electric motor	Position	Support
Burton et al.[48]	Fingers-FE Thumb-FE	Position	Pneumatic actuator	Position	Support
Cao and Zhang[49]	Fingers-FE Thumb-FE	EMG	Electric motor	Velocity	Support
Cempini et al.[50]	Finger-FE	Not listed	Electric motor	Torque	Support
Chiri et al.[51,52]	Finger-E	Position	Electric motor	Position	Support
Delph et al.[53]	Fingers-FE Thumb-FE	EMG	Electric motor	Position, force	Support
Fok et al.[54]	Fingers-FE	EEG	LEA	Position	Support
Goutam and Aw[55]	Finger-F	Force	LEA	Force	Support
Hadi et al.[56]	Fingers-F, Thumb-F	Force	SMA	Force	Support
In et al.[57,58]	Fingers-FE Thumb-FE	EMG, force, position	Electric motor	Force	Support
Iqbal et al.[59–61]	Finger-FE Thumb-FE	Position, force	Electric motor	Position	Support
Iqbal et al.[62]	Fingers-FE Thumb-FE	Position, force	Electric motor	Not listed	Support
Kang et al.[63]	Fingers-FE Thumb-FE	Not listed	Electric motor	Force	Support
Matheson and Brooker[64]	Fingers-FE	Force	Pneumatic actuators	Force	Support
Mulas et al.[65]	Fingers- F Thumb-F	EMG	Electric motor	Velocity	Support
Nycz et al.[66]	Fingers-FE	Position	LEA	Position	Support
Polygerinos et al.[67]	Fingers-FE Thumb-FE	Position	Hydraulic actuator	Force	Support
Saharan et al.[68]	Fingers-FE Thumb-FE	Position	TCA	Position	Support
Sandoval-Gonzalez et al.[69]	Finger-FE Thumb-FE	Position, force	Electric motor	Position, force	Support
Tong et al.[70,71]	Fingers-FE Thumb-FE	EMG	LEA	Velocity	Support
Xing et al.[72–74]	Finger-FE	Position	Pneumatic actuator	Position	Support
Yap et al.[75,76]	Fingers-FE Thumb-FE	EMG, gesture	Pneumatic actuator	Force	Support
Yun et al.[77]	JRTJ2000120x.png Fingers- FE Thumb-FE class="pic-halign"	Not listed	Pneumatic actuator	Force	Support

F: flexion; E: extension; P: pronation; S: supination; I: internal rotation; E: external rotation; Ab: abduction; Ad: adduction; R: radial deviation; U: ulnar deviation; EMG: electromyography; EEG: electro-encephalography; MRF: magnetorheological fluid; SMA: smart material actuator; TCA: twisted coiled actuator; LEA: linear electric actuator.

information collected from the actuation system to provide system feedback was found in 36% of devices. It is also common to use sensors external to the wearable device to collect data during the experimentation process. However, this does not contribute to the real-time control of the device. Within this section, the sensing system will refer to the actual sensor itself and the pre-processing required for the signal to be usable by the control system, this includes additional circuitry required for sensor functionality, filtering, amplification, and rectification of the signal. A visual depiction of how the sensing modalities of the reviewed devices are distributed is shown in Figure 1.

Physiological sensing. Within wearable assistive devices, physiological signal-based sensing is often used to detect signals indicative of a user's motion or force intention. For situations where the user desires to move but is unable to do so, such as nerve or muscular damage, sensing of physiological signals is crucial. From the 23 devices reviewed that incorporate physiological sensing:

- 19 (82.6%) use EMG signals, which measure electrical activity of muscles,
- 3 (13%) use electroencephalogram (EEG) signals, which measure electrical activity of the brain,
- and 1 (0.4%) uses EMG and muscle–force stiffness signals, which measure the change in force of a muscle as it contracts.[26]

The physiological signals collected are often of a small amplitude, susceptible to noise, and can be challenging to classify. Still, 43% of the devices reviewed have incorporated this type of sensor-based feedback.

EMG. EMG is the measurement of the electrical potentials produced at the muscle.[78] These myoelectric signals are a result of the person's intention to move. In wearable applications, surface electromyography (sEMG) is the method typically used to obtain data. sEMG electrodes are placed onto the surface of the skin and electrically coupled to the action potential signals of the muscle, resulting in a voltage measurement of the muscle activity.

All of the devices employing sEMG to collect muscle signals using gelled contact electrodes, abide by Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles standards.[79] This standard ensures electromechanical stability and reduces noise. The electrodes are placed in a bipolar configuration, such that two electrode sites are placed over each muscle of interest. The two channels undergo differential amplification to eliminate the common-mode signal, allowing the changes in muscle activity to be more evident. Use of hydrogel ensures that the electrode properly adheres to the arm, preventing sensor movement and motion artifacts.

In each of the studies, sEMG signals were recorded from the muscles of interest, depending on the limb segment assisted by the device. In the nine studies where sEMG was used to control a hand orthosis,[42,46,49,53,57,58,65,66,70,71,75,76] five report the muscles from which signals were collected. These were: *flexor digitorum superficialis,*[65] *flexor policus longus,*[65] *flexor digitorum profundus,*[53,70,71,75,76] *extensor digitorum communis,*[49,53,70,71,75,76] *extensor digitorum superficialis,*[49] *abductor pollicis brevis*, *biceps brachii*, and *triceps brachii.*[70,71] The motion supported by these devices was the flexion–extension of the fingers and the thumb.

Eleven systems use sEMG for control of the elbow joint.[11,20,22–24,28,30,32,34,40] Nine of these systems were concerned only with the flexion–extension motion of the elbow and eight of these reported the muscles from which signals were obtained. In accordance with
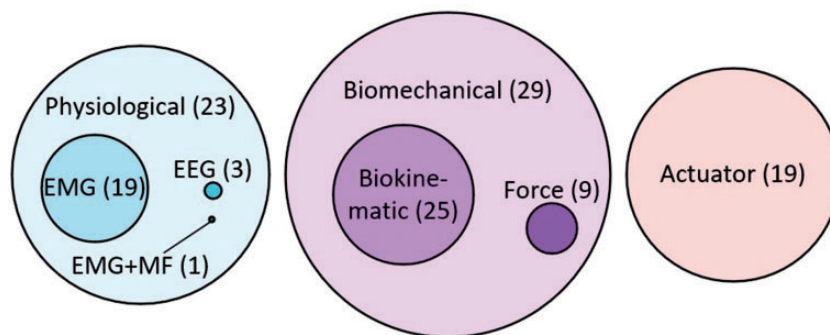
Figure 1. The distribution of sensing modalities across the reviewed devices. Electromyography (EMG), electroencephalography (EEG), and EMG and muscle–force (EMG+MF) sensing are subcategories of physiological sensing, while biokinematic and force sensing are subcategories of biomechanical sensing. In the case of biomechanical sensing, some devices used both biokinematic and force sensing. The size of the bubbles in this figure is scaled to show the relative difference between the number of devices that used each of the sensing modalities.

the arm's physiology, every system placed electrodes over the *biceps brachii* and *triceps brachii* muscles. Additionally, two of the systems recorded from the *brachioradialis* and one recorded from each the *anconeus* and *flexor carpi ulnaris*.[20,32]

Among the two systems that also supported the pronation–supination motion of the forearm, both recorded from the *biceps brachii*, *triceps brachii*, *brachioradialis*, and *flexor carpi ulnaris*.[20,40] One of these devices looked at muscles from the *extensor digitorum* and *palmaris longus*, which are not typically associated with motion of the forearm or elbow.[40] However, this device analyses the flexion–extension and ulnar–radial deviation of the wrist joint.

Due to the erratic nature of the sEMG signal, it must undergo a relatively large amount of pre-processing compared to other signals before it can be used as input to a control system. Among the devices reviewed, 13 mention some pre-processing details.[11,22–24,28,32,34,40,49,53,57,58,65,70,71] Amplification noted in the reviewed studies was as follows: Tang et al. used an unspecified preamplifier,[32] Stein et al. applied a gain of 300,[11] Tong et al. applied a gain of 800,[70] and Delph et al. used two gain stages, a 10 times gain stage followed by a selectable gain stage.[53] The filters used ranged both in type and cutoff frequency, as described among 11 devices.[11,22,23,28,32,34,40,49,53,65,70,71] Fourth-order high and low pass filters were a popular choice, used by four devices.[28,32,34,53] Wang and Huang used a band pass filter with a range of 100–1000 Hz,[34] Delph et al. chose a high pass filter with a cutoff frequency of 10 Hz and a low pass filter with a cutoff frequency of 750 Hz,[53] and Kyrylova used a 10 Hz high pass filter.[28] Ando et al. chose a third-order 18 dB/octave high pass filter and an eighth-order elliptic filter with a cutoff frequency of 550 Hz.[22] Other filters used include Stein's band pass filter with a range of 10 Hz–3.12 kHz,[11] Tong's 10–500 Hz band pass filter, Vaca Benitez's et al. variance filter,[23] Xiao and Menon's use of fourth-order autoregression,[40] and Mulas et al.'s moving average filter.[65]

Rectification of the EMG signal was reported by Tang et al.,[32] and signal shifting circuits were used by Cao and Zhang and Delph et al. to shift the voltage recorded into the range supported by the analog-to-digital converters (ADCs).[49,53] Tang, Vaca Benitez, Xiao, In et al., Desplenter et al., and Kyrylova all calculated the root mean square (RMS) of the filtered EMG data.[23,24,28,32,40,57,58] The EMG sampling rate among the devices reviewed ranged from 250 Hz[57,58] to 8 kHz.[34] Furthermore, the sensor systems surrounding EMG data collection for wearable assistive devices varied greatly.

EEG. EEG is a measurement of the brain's electrical potentials from the scalp.[80] These signals were used to control three of the mechatronic systems reviewed. All three publications report using the wireless EPOC[+] EEG headset (EMOTIV Inc., USA) to record signals across the frontal and temporal lobes.[21,29,54] The system consists of 14 saline-based wet electrodes in 10–20 standard locations, and two reference electrodes in the noise cancellation P3/P4 location attached to a headset that wraps around the exterior of the cranium. Fok et al. state that the EPOC device design did not fully cover the motor cortex.[54] The headset operates at a 0.2–43 Hz bandwidth with built-in 50 and 60 Hz digital notch filters to avoid power line interference. A digital fifth-order Sinc filter was also used to prepare data for analysis using the proprietary Cognitiv Suite software (EMOTIV Inc.). In these studies, the EEG headset was used to control elbow flexion–extension, forearm pronation–supination,[21,29] wrist flexion–extension, radial–ulnar deviation,[21] and finger flexion–extension.[54] These studies indicate that the system was able to provide clear and accurate sensor data capable of controlling wearable assistive devices to support the elbow, wrist, and hand.

The use of EEG allows a user with limited mobility, or even with an amputation, with an accessible way to provide biofeedback during physical rehabilitation. However, the use of this system to determine motion intention presents challenges. The spatial resolution of the electrode with respect to the underlying neurons makes it difficult to determine the exact location of electrical activity. Therefore, significant amounts of crosstalk occur among electrodes while obtaining signal data, and only two simultaneous thoughts can be classified.[21] Another pitfall is the efficacy of tracking intention. It is impossible for a researcher to evaluate the efficacy of the system when the user's intention cannot be confirmed and may be considered hearsay.[29] Xiao et al.[21] and Looned et al.[29] have reported the need for user training sessions to teach subjects how to control the devices with their thoughts. In the future, EEG signals can be improved through the use of additional processing to eliminate artifacts, such as blinking. Work can be done to decouple the EEG signals from one another and from other biological signals recorded from the body, either through digital classification techniques or through hardware adjustments.

Muscle–force measurement. Only one of the reviewed devices measured muscle–force stiffness as biofeedback. Kim et al. demonstrated the efficacy of this technique using piezoelectric resistive pressure sensors to control the flexion–extension movement of the elbow joint. The sensors within this device were attached to a band and positioned over the *biceps*

brachii, *triceps brachii*, *flexor carpi ulnaris*, and *brachioradialis*, which are consistent with reported sEMG electrode locations for monitoring of this gross motion. The study reports that the use of muscle–force stiffness measurement was more accurately able to trigger a threshold-based actuation system than EMG, was less susceptible to noise and muscle fatigue, and did not require significant or uncomfortable preparation. The work did not detail the signal processing required or potential drawbacks of this sensing method. Still, extensive validation of muscle–force stiffness measurement does not yet exist.[26]

Biomechanical sensing. Biomechanical sensing refers to the outward mechanical motion that arises from human body processes, such as the measurement of the limb's kinematic and dynamic properties. These methods of sensing are easier to integrate within the system than physiological sensing technologies, as they are often compact, self-contained, less sensitive to placement location, and less expensive. Accordingly, 55% of the devices incorporate biomechanical sensing into their systems. Due to the reliance of biomechanical sensing on the user being able to produce motion, limitations occur when the user suffers from paresis or is unable to produce the desired biomechanical signal.

Biokinematic sensing. Biokinematic sensing refers to the measurement and collection of kinematic data that arises from human motion. Biokinematic-based sensing was found within 86% of devices that use biomechanical sensing techniques. Information, such as joint angle, linear and rotational position, velocity, and acceleration, are used to provide biofeedback to devices using position-based closed-loop control systems.

Many types of sensors can be incorporated under the position sensing umbrella. Seven of the devices opted to use potentiometers, which are capable of tracking rotational or linear motion along the joint or limb segment. Four devices measured data along the elbow,[16,25,32,40] five tracked the wrist or hand,[16,29,40,65,69] and one tracked the shoulder and forearm.[16] Potentiometers are frequently used in mechatronic systems due to their low cost, lack of susceptibility to electromagnetic interference, and ease of integration. No additional circuitry or power connections are required to provide an absolute position reading within a particular range.

Another sensing modality used for human-based kinematic measurements is the encoder, which was incorporated into six of the reviewed devices.[17,23,34,39,62,72–74] Encoders are used to determine elbow position in three devices,[17,23,34] shoulder position

by Brackbill et al.,[17] hand position by Iqbal et al.[62] and Xing et al.,[72–74] and wrist position by Taheri.[39] Some of the sensors used required a signal conditioning circuit and analog-to-digital conversion to provide absolute angular measurement. Furthermore, some were immune to degradation and environmental concerns, including vibration, temperature, and contamination. Xing et al. note the use of an unspecified filter and an ADC,[72] while the other studies did not detail the remaining components of the sensing system.

Various types of bend sensors, made from conductive ink on a flexible laminate, were used by five devices to determine joint angles and deflection. The devices made by In et al. and Kang et al. used this modality to generate data related to the wrist.[57,58,63] The remaining three systems use bend sensors on the finger joints.[35,42,47] The full sensing system is described by Aubin et al., who reported that the output of bend sensors underwent voltage division, impedance buffering, and amplification with an adjustable 1–10 gain, before the signals were digitized using a 10-bit ADC.[47] Filtering and analog-to-digital conversion were not described in any of the other publications involving bending-based position sensors. The fabrication of bend sensors is fairly robust, low cost, and experiences little hysteresis or noise. However, these sensors are susceptible to signal drift.

Another popular kinematic-based sensor is the inertial measurement unit (IMU), which consists of one or more of the following components: accelerometers, gyroscopes, and magnetometers. These types of sensors may be combined in order to compensate for one another's shortcomings. For instance, gyroscopes experience significant drift, which can be compensated by using the accelerometer and magnetometer. Seven devices used some combination of the aforementioned components. Of these devices, four used gyroscopes,[19,25,29,41] five used accelerometers,[16,19,28,37,41] one used magnetometers,[41] and one used an unspecified IMU.[18] Six of the systems collect elbow data,[16,18,19,25,28,29] two collect shoulder data,[16,18] one collects wrist data,[41] and two measure hand data using IMUs.[16,41] IMUs are generally inexpensive, compact and have a wide breadth of possible applications. However, more computational complexity is required than with other kinematic sensors to achieve information with efficacy. Within the devices reviewed, three mention filtering the sensor output.[19,25,28] Both Herrnstadt and Menon, and Rocon et al. provide filter specifications used for the gyroscopes in their devices. They used a sixth-order elliptic high-pass filter with a 2 Hz cutoff[25] and a high-pass filter with a cutoff of 0.3 Hz and a low-pass filter with a cutoff of 25 Hz,[19] respectively. Meanwhile, Kyrylova reports filtering accelerometer signals with a second-order

Butterworth high-pass filter with a 2 Hz cutoff frequency.[28]

Force sensing. In addition to kinematic or position sensing, force-based sensing is also frequently used in wearable mechatronics for the upper limb. The relationship between joint force and torque makes measurement of interaction forces between the limb and the device an attractive quantity to incorporate into a closed-loop controller. While many of the studies mention the use of force sensing, nine incorporate human driven forces into a closed-loop controller.[23,42,51,52,55,59–62,64,69,72–74] Five of these systems incorporate position-based biofeedback, as well.[23,42,62,69,72–74]

Of these nine devices, one tracks elbow data and the others track hand data. Vaca Benitez et al. track interaction between the elbow and the device, using a miniature inductive force sensor.[23] The inductive force sensor is compact, lightweight, resistant to shock and vibration, short-circuit protected, and contains an amplification system. However, this sensor is more expensive than other force sensing technologies and only one can be used without experiencing interference.[23] The force induced by the arm on the device is measured in order to calculate the amount of torque required to control the system.

The other eight systems track forces exerted on the orthosis by the hand.[42,51,52,55,59–62,64,69,72–74] All of these devices sense force through the change in resistive behavior due to mechanical deformations of the sensor. The two devices presented by Iqbal et al. used load cells attached to strain gauges, which are inexpensive and simple to manufacture but need protection from the environment. Strain gauges require strict signal conditioning and are often arranged as a Wheatstone bridge. Changes in resistance result in an imbalance and consequently a change in the voltage seen across the bridge.[59–62] Typically, this representative voltage is then amplified and digitized within the sensor or electronic system. Sandoval-Gonzalez opted for flex-force sensors connected to a force sensing circuit, which generates a frequency based on an op-amp's perceived capacitance and converts it to a representative voltage.[69]

Three of the remaining devices used force sensing resistors (FSRs).[42,64,72–74] FSRs are all compact, flexible, inexpensive, and experience low noise and long-term stability. However, they tend to have a poorer dynamic range and less accuracy than strain gauges. FSRs are also typically nonlinear and exhibit significant hysterisis.[81] The signal conditioning required is voltage division and buffering, but these components of the sensing system were not described in the reviewed publications, aside from mention of

amplification by Matheson and Brooker.[64] This force-sensing modality requires calibration before use.

Within seven of the hand-assistive devices that used force-based sensors, the sensors were placed beneath the mechanical structures of the device to determine the interaction force exerted between the finger and either the device or an external object. The eighth used silicon piezoresistive sensors to measure palmar interaction force.[51,52]

Actuator sensors. For some of the wearable assistive devices, measurements of non-biological quantities were used to provide feedback to the system. Eighteen of these devices collected information from the actuators to compare the performance against the expected behavior.[17,19,27,28,30,31,34,37,39,40,51,52,59–62,64,66,67,72–76]

When discussing non-biological feedback, the type of sensing becomes dependent on principles of operation of each actuator. Designs incorporating motors can rely on the same quantities as those measured from the human body, such as position, speed, and force within the actuated mechanisms. Ten of the devices that used feedback from the actuator used kinematic-based sensing. Six of these report the use of encoders placed on the motors allowing them to determine the rotational position and speed at which it operates.[17,28,34,51,52,59–62] Six other systems opted to track the linear position of the actuator.[31,34,37,39,64,66] Three of these devices employed linear potentiometers attached to springs and Bowden cables to measure position.[34,39,66] Kazi et al. and Matheson and Brooker used a linear variable voltage transducer (LVDT) for position sensing of piezoelectric and pneumatic artificial muscle (PAM) actuators.[37,64] Matheson and Brooker also reported amplification of the LVDT output.[64] Ren et al. converted the current running through the motor into the speed of the motor through a model of the actuator.[31]

The behavior of pneumatic actuators can be evaluated better through the measurement of pressure, as they function through the conversion of compressed air energy into mechanical motion. Six of the reviewed devices used pressure sensing as feedback to the control system. Five of the instances attached the sensor directly to a pneumatic actuator, with one reporting use of silicone pressure sensors at the diaphragm,[67] one measuring pressure in the control valve,[72–74] one unspecified[30] and two measuring the cylindrical chamber pressure of the actuator.[39,75,76] The final device uses cable-tension sensors made from strain gauges.

Other dynamic actuator-based measurements are used for feedback in three additional systems. Xing et al. used force sensors to measure PAM forces in the finger and thumb.[72–74] This allows for increased

information and control of the actuator behavior, by returning information from each joint. Like with biological quantities, strain gauges can be integrated into the device. For instance, Rocon et al. used these sensors to measure forces perpendicular to the motor shaft.[19] While this information was later converted into torque values, Xiao et al. directly measured the torque along the axis of rotation coincident to the wrist flexion–extension and ulnar–radial deviation movements. KleinJan measured resistance within shape memory alloy wire actuators as an input to the control system.[27] All systems using non-pressure-based dynamic measurements, included in this review, focus on the hand or wrist.

Of these 18 devices, 3 use the measured actuator data as the only control input.[27,31,67] Conversely, 2 of the remaining devices use physiological quantities[30,75,76] and 10 use biomechanical properties as other inputs.[17,19,28,37,39,51,52,59–62,64,72,73] There are three devices that use both physiological, biomechanical, and on-actuator sensors.[34,40,66] The related sensing systems of the on-actuator sensors are not often described. As a result, information is limited with regards to filtering, amplification, rectification, data conversion, and other pre-processing techniques.

Overall comments and future directions. Through the review of existing devices, it is clear that a myriad of sensing modalities and quantities are incorporated into wearable assistive devices. Data are collected from both biological processes, such as physiological signals or mechanical motion of the limb, from the actuator, or both. However, many devices do not use sensor signals to dictate the behavior of the control and actuation systems. Sensor-based feedback was not used by 13% of the reviewed devices and appears to rely on predetermined motion paths or open-loop control.[36,43,48,50,56,68,77] This may limit the precision of these systems and make them less responsive to the immediate needs of the user.

Multi-modal sensing seems prevalent within wearable assistive devices, based on the devices reviewed. Through the use of multiple sensing modalities, a fuller profile of the user's motion or intention can be provided. This allows accuracy and fatigue to be further characterized, and to track muscle health or range of motion over time. The sensors placed on the actuators provide insight into the functional output of the controller and the sensors measuring biological quantities are able to incorporate data related to the actual condition of the user. Realizing the potential benefits of multi-modal sensing, eight researchers have expressed the desire to incorporate additional sensing modalities into their future work.[16,32,36,49,55,57,58,64,75,76] Three of those eight researchers specifically noted their interest

in exploring the use of EMG signals in future work[36,55,64] and two expressed the desire to add more EMG electrode sites.[24,65] These researchers may be seeking more information to input to the controller. However, it is uncertain whether additional sensors will improve the system performance until they are implemented.

Actuation

The actuation system used for wearable assistive devices is one of the vital components of the device as it provides the motion and torque/force to assist the user. An actuation system consists of the actuator and a method for transmitting the force to the required joints. The transmission method allows the actuator to be mounted remotely instead of attached directly to the joint and also change the direction of motion. For wearable devices, two main requirements related to the actuation are the force or torque required to complete the motion task and the range of motion of the joints involved in the motion task. Actuators are available that can fulfill or exceed these requirements, but often fail to meet size and weight constraints that enable portability. Therefore, a major objective is to reduce the weight of the device, which is partially done through minimizing the size of the actuation system, while meeting the motion requirements.

Based on the difficulty of meeting actuation requirements, a wide variety of different actuation systems have been proposed in the reviewed devices. The types of actuators found in these devices are direct current (DC) motors, pneumatic actuators, hydraulic actuators, electromagnetic friction brakes, magneto-rheological fluid-based actuators, shape memory alloy actuators, twisted coiled actuators (TCAs), and piezo-electric actuators. The frequency of use of each of these actuation systems categorized by the targeted limb segment is shown in Figure 2. DC motors are the most commonly used actuator (62% of devices), followed by pneumatic actuators (21% of devices). The remaining types of actuators are only used once or twice. The popularity of DC motors is likely due to being easier to implement than other actuators, while also being capable of providing the required actuation. However, DC motors are not a perfect or global solution and this has led to implementing less commonly used actuators.

Actuator designs for the hand focus on gripping force as a requirement instead of torque requirements for each of the hand and finger segments. In et al.[58] suggest that a pinch force of 20 N and a wrap grasp force of 40 N would be sufficient to execute some ADLs. Of the devices that actuate the shoulder, elbow, and wrist joints, 41% listed the torque applied
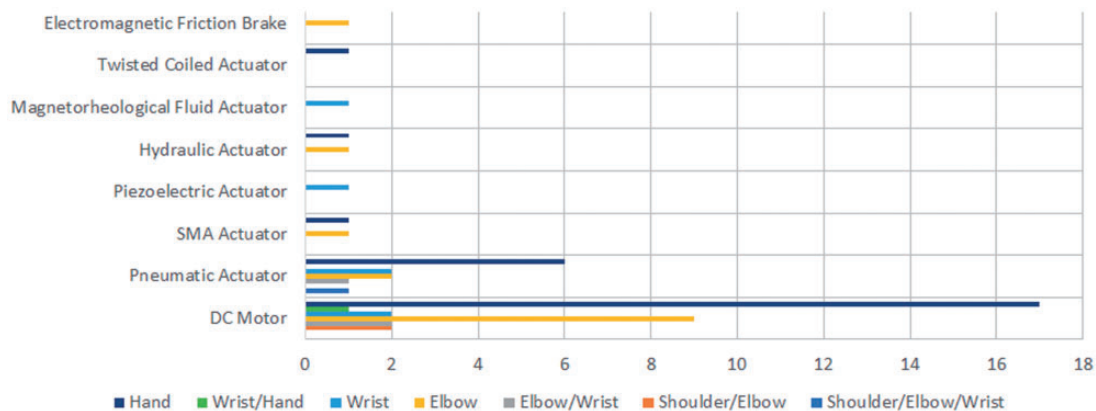
Figure 2. Frequency of actuator type based on the targeted body segment.
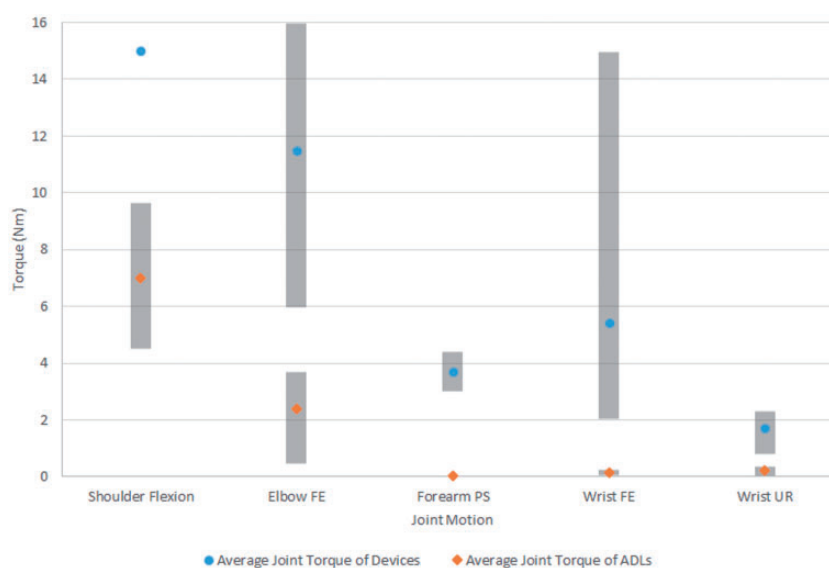
Figure 3. Average and range of torques of the reviewed devices compared to average torque values for activities of daily living (ADL) across different joints. The torque values of ADLs are taken from a study by Rosen et al.[82]

to the joint.[16,21,23–25,28–31,36,40] Figure 3 shows the average torque and range of torques for each joint contrasted to the torque values for healthy human joints performing ADLs. In device designs that list torque specifications, the joint torque of these devices are able to meet the torque demands for ADLs as gathered from the study performed by Rosen et al.[82]

DC motors. In this review, 62% of devices use a DC motor for actuation. Most notably, DC motors have been used to actuate each of the upper–limb segments in this review. The large selection of commercially available DC motors is what makes this type of actuator so popular. In general, implementation of these actuators is much easier compared to most other types of actuators. Of the devices employing DC motors, 42% used brushed DC motors,[11,34,40,43,49–54,59,60,62,63] 24% used brushless DC motors,[17,19,23,24,28,31,41,58] 6% used both brush and brushless DC motors,[21,29] and 28% do not specify the type of DC motor that is used. Rotational motion is provided by 82%[11,17–19,21–24,28,29,31,33,34,40,43,47,49–53,58–60,62,63,65,69] of these DC motors and the remaining 18% provide linear motion.[36,46,54,55,66,70] The rotational DC motors all require a gearhead to increase the torque output, which is transmitted to the required joint through either cables, Bowden cables, gears, or linkages. The linear motion DC motors are all connected to the actuated joint using linkages.

For wearable assistive devices, brushless DC motors are generally a better choice over brushed DC motors. The brushed DC motors have well behaved speed–torque characteristics are adaptable, and are easy to control, which can make them a great option for

prototyping and sub-system evaluations.[83] However, brushless DC motors have reduced maintenance, higher output power, better heat dissipation, and the ability to maintain or increase torque at different speeds.[84] The downside to brushless DC motors is that they are more expensive than brushed DC motors and the control is more complex.

Pneumatic actuators. Pneumatic actuators were the second most commonly used actuator in the reviewed devices. Compared to DC motors, pneumatic actuators offer a higher power-to-weight ratio, excluding the actuator infrastructure, and compliant actuation. Of the 12 devices using pneumatic actuators, nine used PAMs,[16,20,26,32,35,42,48,64,72] 2 used pneumatic bending actuators,[75–77] and 1 used a pneumatic cylinder actuator.[39]

PAM actuators consist of an inflatable bladder inside a braided mesh that is clamped on both ends. When the bladder is inflated, it results in a contraction of the PAM due to the constraints of the structure. In the listed devices, these actuators are placed along the forearm or upper-arm, such that a pulling force is applied to actuate a joint. Some devices used PAMs to actuate the joint in one direction,[16,42,48,72] while others use an antagonistic setup to actuate in opposing directions.[20,26,32,35,64] The main advantages for PAMs in a wearable device is that they are generally lighter than other actuators and are mechanically compliant. In addition, PAMs do not require a fixed joint center, allowing more variation in the design of devices that employ them. The disadvantages to PAMs are that they have a slow and nonlinear dynamic response, which makes them challenging to control.[10,85]

Yap et al. and Yun et al. have used pneumatic bending actuators to provide assistance for hand motion.[75–77] In these two devices, the actuators are attached along the fingers using either Velcro with a glove or straps, respectively. When the actuator is inflated, it causes a bending force. This actuator only provides a bending force in one direction, which means that it can only assist with flexing the finger, but not extending it. The advantage of this type of actuator is that it is placed directly on the finger joints, so no additional parts are needed for transmission of forces.

The pneumatic cylinder actuator incorporated by Taheri can generate a push or pull force that is used for tremor suppression.[39] The ability to provide force in both directions is an advantage that this type of actuator has over the PAM and pneumatic bending actuators, which can only provide force in one direction.

Hydraulic actuators. Hydraulic actuators operate similarly to pneumatic actuators, but use a liquid for power transmission, instead of compressed air. In this review, hydraulic actuators were implemented in two of the devices. Polygerinos et al. use a custom made flexible fluidic actuator for assistive hand rehabilitation,[67] while Pylatiuk et al. developed a custom made hydraulic bending actuator for assistive elbow rehabilitation.[30] The advantages of hydraulic actuators are higher power density and higher efficiency than pneumatic actuators. However, hydraulic actuators have the potential to leak liquid and require more infrastructure to function, such as a pump and reservoir. This creates challenges to find biocompatible fluids that meet functional requirements and infrastructure that will not restrict the portability of the system.

Electromagnetic friction brake. The electromechanical friction brake uses an electromagnetic force to apply a frictional force on the rotating disk, which will slow or stop motion. Herrnstadt and Menon use an electromagnetic friction brake for a tremor suppression device.[25] This device operates by switching between applying no torque and a resistive torque, whose values were not specified. The electromagnetic friction brake is only useful for applications where a motion produced by the user needs to be resisted, such as tremor suppression. A big limitation to these brakes is that the best performance occurs in a range that is near the maximum output torque. The output torque is generally unstable when it is not in this upper end of the torque range. Therefore, application of this actuator relies on the condition that the required suppression torque varies less than the stable range of output torque.

Magnetorheological fluid actuators. Only one device in this review used a magnetorheological fluid actuator to provide tremor suppression of the wrist.[38] Magnetorheological fluid actuators use a magnetic field to vary the viscosity of the magnetorheological fluid. By altering the viscosity of the fluid, the actuator can be used to slow or stop movement of a joint. As with electromagnetic friction brakes, this type of actuator can only be used to resist forces. As a result, magnetorheological fluid actuators are best suited for suppression of undesired motion. The advantage of this type of actuator is that it has a fast response to control inputs. However, the large weight of these actuators limits the wearability of devices employing them and the actuators themselves have an impact on voluntary motion.

Shape memory alloy actuators. Shape memory alloy actuators were implemented by two of the reviewed devices.[27,56] Both of these devices incorporated shape memory alloy cables to drive joint motion. Shape

memory alloy cables undergo a phase transformation from a flexible state (Martensite) to a rigid state (Austenite). They can be trained to remember a desired shape upon heating. The advantages of this type of actuator are that it has a silent actuation and a simple structure. However, shape memory alloy cables exhibit nonlinear characteristics, low energy efficiency, and a slow response to control inputs. The low energy efficiency is due to the cables being heated through Joule heating, while the slow response is caused by differing heating and cooling rates. Reducing cooling time of the cables would likely require increasing the weight and the cost of the device. Further research is required to improve these actuators and capitalize on their benefits.

Twisted coiled actuators. TCAs are a more recent technology to be used in wearable assistive devices. Saharan et al. uses TCAs in a hand orthosis in order to assist finger motion.[68] TCAs consist of a fiber that has been twisted and coiled, while under tension. When heat is applied to the fibers, TCAs can contract by up to 49% of their initial length.[86] Additionally, the energy density has been recorded as high as 5.3 kW/kg,[87] which is significantly higher than human muscle (200 W/kg).[88] However, similar to the shape memory alloy cables, the downside to this type of actuator is the low energy efficiency, due to the inherent energy losses of a thermal actuator. Furthermore, TCAs require much higher temperatures, than human tissue can withstand, to function. For example, Saharan's design used temperatures up to 250°C. Therefore, thermal protection is required in order to deploy this actuation technology in wearable applications.

Piezoelectric bimorph actuators. Piezoelectric bimorph actuators were implemented in one of the wearable assistive devices. Kazi et al. use a piezoelectric bimorph actuator to suppress tremors occurring in the wrist joint.[37] This actuator consists of two piezo plates bonded together with opposite polarity, such that one expands, while the other contracts, causing it to bend. Using piezoelectric bimorph actuators provides developers with a fast response and low power actuation. However, the small range of motion produced by these actuators limits the opportunity for their application. Kazi's device did not describe any specifications of the actuator, making it difficult to compare against other types of actuators.

Actuator placement and transmission. The placement of actuators falls into one of the following three categories: on the device joint, near the joint, and away from the joint. Some of the lighter actuators, such as the piezoelectric bimorph actuator and the hydraulic bending actuator, are capable of being directly attached to the joint.[30,37] Being placed on the joint removes the need for additional transmission and helps achieve a lower overall system weight. Many of the reviewed devices place the actuator near the joint of interest. However, this design decision requires a transmission structure in order to actuate the joint. The transmission types for actuators placed near the joint include gears,[19,22–25,28,31,69] cables,[47,64,65,68,72] linkages,[54,70] or a combination of these transmission methods.[21,33,34,40,43,48–50,52,53,55,57,59,62,63] The downside to having actuators near the joint is the required transmission will increase the size and weight of the device. Furthermore, transmission systems, typically, are not 100% efficient creating power losses between mechanisms. A few of the reviewed devices place the actuator away from the actuated joint, either on the back of or supported separately from the user. In this review, devices with actuators placed on the back use either cables with pulleys[17,18] or Bowden cables[11,53,66] for transmission of force, whereas the devices with the actuators placed away from the body use Bowden cables.[47,49,63] The advantage of placing the actuators on the back is that it is easier to support the weight on the torso instead of the arm. Devices with the actuators away from the user are easier for the user to support, but they can limit the mobility of the user. A breakdown of the actuator type, based on placement, is shown in Figure 4.

Overall comments and future directions. Actuation systems are critical components of wearable assistive devices, for without them no physical assistance can be generated. After examining the actuators, it is clear that the application plays an important role in actuator choice. DC motors and pneumatic actuators are the most common across the reviewed devices. However, seven other types of actuators have been proposed. The variety of actuation systems suggests that no one type of actuator can provide a global solution for wearable assistive devices.

Two of the main challenges with the reported devices are the size and weight of the actuators, and the lack of actuator requirements and specifications. First, minimizing the size and weight of the devices can be partly achieved by reducing the size or weight of the actuation system. Two potential avenues for reducing these aspects include continuing to improve existing actuators and consider new ways to implement the actuators. Currently, most devices use DC motors due to their reliability and ease of implementation, but they are bulky and heavy. Other emerging types of actuators may reduce the size of devices, but are not as reliable or easy to control. As a result, both types of actuators can benefit from continued
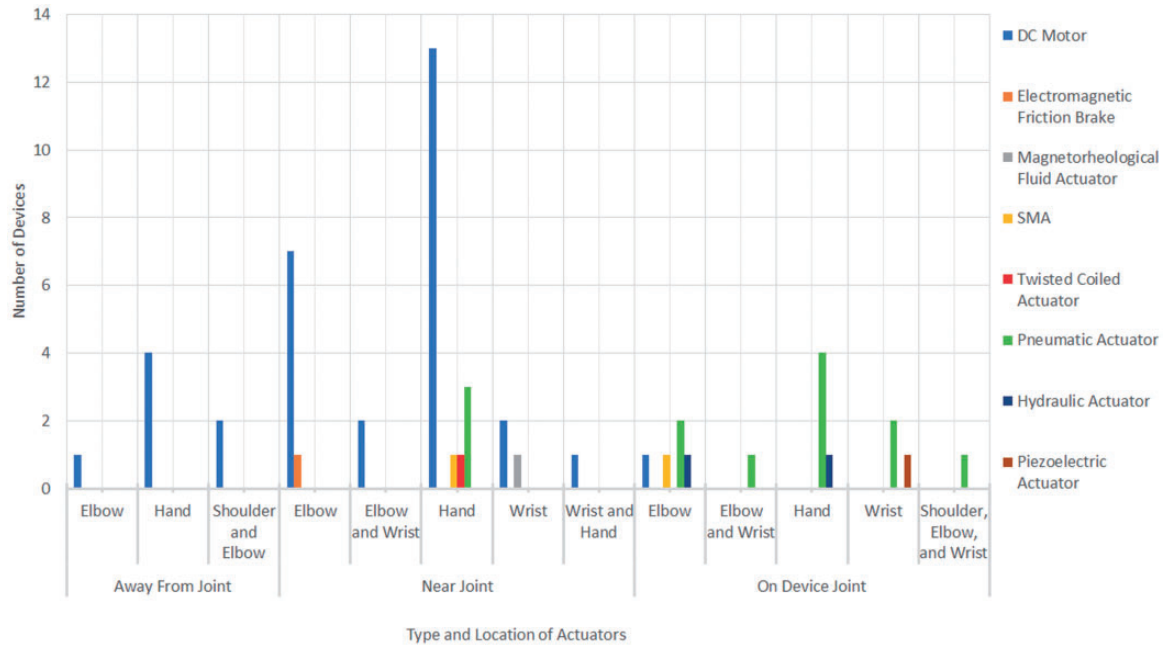
Figure 4. Frequency of devices and actuator types for each actuator location.

improvements. The other avenue is to develop new ways to implement the actuators. This includes finding ways to reduce the number of actuators used or positioning the actuators such that the weight is less of a burden on the user. Second, most of the reviewed devices do not provide all of the necessary information for developers to make an informed decision about their usage. Without that information, it can be difficult to evaluate the actuation and find ways to improve upon it. Ideally, researchers would provide the force or torque range, range of motion, speed, and weight of the actuation system, as well as actuation requirements for the intended application. This is especially important as it can increase the opportunities to study new actuation technologies.
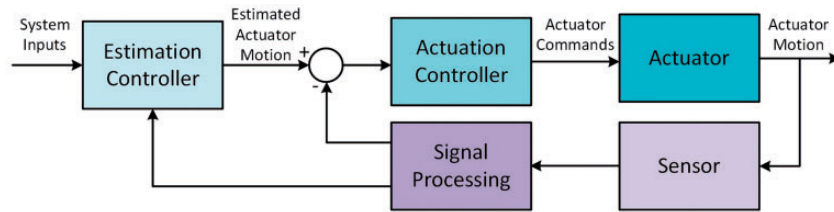
Control

The control system of a wearable assistive device manages the behavior of the actuator using a control pathway with or without the help of sensory input. The input, output, feedback state, and strategy (internal model) are important aspects of these control systems and can be used to categorize them.[89] It was found that control systems were developed to use physiological signals (such as EMG), biomechanical signals (such as joint position), or a combination of these two types of signals as inputs. Systems incorporated both closed-loop and open-loop feedback strategies to regulate position, velocity, acceleration, force, or torque outputs. Finally, their internal models included proportional–integral–derivative (PID) control, threshold control, sliding-mode control, machine learning control, biomechanical model control, empirical model control, and other control methods.

In this section, the review of the control system of the wearable assistive devices is presented from the perspective of their internal models. A generalized control system model is presented in Figure 5. Due to insufficient information provided in some of the reviewed manuscripts, the control systems of 19% of the devices were unavailable to be included in this section.

PID control. PID controllers and their variants have been the mainstay of the control system of wearable assistive devices. A PID-based controller operates based on the error between the measured signal and the desired signal, hence it does not require a complex mathematical realization of the plant. Its advantages in computational load, control accuracy, simplicity, and robustness have facilitated the development of wearable assistive devices in recent years.

Pylatiuk et al.,[30] Mulas et al.,[65] Desplenter et al.,[24] Aubin et al.,[47] and Cao and Zhang[49] adopted closed-loop proportional control in their wearable exoskeleton devices. These control systems manage the speed of the actuation systems to be proportional to the measured EMG intensity. This strategy provides more controllability to the user than the threshold control system. Although these devices do not estimate the user's

Figure 5. A generalized control system block diagram for wearable assistive devices. In this example, estimation controllers are typically developed as threshold, sliding-mode, machine learning, biomechanical model, or empirical model controllers, while actuation controllers are commonly PID-based controllers. The control system architecture and details of each block will vary based on the needs of the specific device or application.

intended motion, the reduced complexity of these controllers makes them more suitable for implementation with lower-cost embedded computer systems.

Brackbill et al.,[17] Lessard et al.,[18] Ren et al,[31] Andrikopoulos et al.,[35] Chiri et al.,[52] and Wu et al.[74] adopted closed-loop PID control in their wearable exoskeleton devices. The control accuracy of these devices is reduced largely in the presence of low frequency disturbances, which is a non-negligible issue in wearable assistive devices. The jitters from the controller output may also reduce overall control accuracy by introducing unwanted interactions from other inputs as disturbances. Furthermore, these control strategies require improvement in adaptability for applications with different users and scenarios, such as incorporating physiological signal-based control, or adaptive control.

Lastly, Wu et al. developed a self-tuning fuzzy PID for a wearable rehabilitation device. The parameters of the PID controller can be tuned adaptively according to the error. Such control systems not only maintain the advantages of the conventional PID controller, but can achieve higher control performance and accuracy.

Threshold control. Several of the articles reviewed implemented a type of control called threshold control. This category of control applies to EMG-based wearable exoskeleton devices, which required the determination of a percentage threshold with respect to the user's maximum voluntary contraction. A typical maximum voluntary contraction test is required to calibrate the system. The devices are activated when the detected EMG signal exceeds the threshold and actuated at a predefined speed. Tong et al.,[70,71] Yap et al.,[76] and Delph et al.[53] chose 20% to 30% of the maximum voluntary contraction as the threshold.

Xiao et al. developed a closed-loop threshold-controlled brain–computer interface (BCI) for stroke rehabilitation.[21] This system is designed to identify one conscious motion command at a time to activate the different movements of the device. For each conscious motion command, a sequential control scheme was predefined by the researchers. The commands consist of

three stages, which are pre-decision, decision, and post-decision. A threshold was predefined for each stage to compare with the magnitude of the user's EEG signal, in order to determine the intention of the user.[21] If the average activation power is beyond the threshold, then the device is actuated. This control scheme was tested on one healthy volunteer. Although the results showed good performance when distinguishing between a conscious thought and the neutral state, the fact that they have only tested on a single subject is a considerable limitation. More subjects are required to validate the proposed control system. In addition, this system requires a long time-window to distinguish a valid conscious command, which is a drawback for real-time control, since it may cause undesired actuation of the user's joint.

Similarly, Fok et al. adopted the closed-loop threshold control in a wearable assistive device for stroke rehabilitation.[54] Instead of using a sequential control scheme, this system developed a least mean square adaptive filter to match its gain to the change of the input signal. Although the accuracy still requires further improvement, the author claimed that the real-time performance and the accuracy of the system exceeded previous studies and that this device holds the possibility for in-home treatment.

Sliding-mode control. Another type of control system is called the sliding-mode controller (SMC). Polygerinos et al. developed a rehabilitation glove using an SMC.[67] This control system is constructed by one piecewise function that describes the general form of the device. Although such a controller does not require an explicit model of the system, it requires the system's behavior to be continuous and smooth, which is not the general case in human–machine interactions. Furthermore, this control strategy requires the actuators to cope with high frequency control actions, which could affect the product life of the system for patient use.

Machine learning control. The aforementioned control systems are undoubtedly simple control strategies to

use for a wearable assistive device. However, this simplicity limits the ability for the user to control the device, since the controlled parameters, such as speed and force, are not adaptive. To improve the user controllability, artificial intelligence has been implemented to estimate the user's voluntary motion.[32,40] For example, Tang et al. adopted a closed-loop back-propagation neural network to estimate the target joint angle.[32] An EMG-to-angle model was built for pattern recognition in the back-propagation neural network, and the RMS of the EMG was used as the input to the classifier. The evaluation of the control scheme showed that the proposed system provides an effective way to estimate the user's motion in real time, but the estimation error varies with different motions. Moreover, every subject has to go through a procedure to train the system to recognize their input signals.

A more complex closed-loop neural network-based control system and a support vector machine-based control system were developed and compared by Xiao and Menon.[40] To increase the accuracy of the classifiers, six features were calculated from the raw EMG data: the RMS value, four coefficients of a fourth-order auto-regression model, and the wavelength. The extraction of these features created a time delay of 0.124 s. The evaluation of the two classifiers showed that support vector machines had better performance than feed forward neural network, and could identify the levels and directions of the user's wrist torque better. The authors mainly studied the application of artificial intelligence in estimating the torque of the user's joint. However, it is not sufficient to apply such technique in an assistive device without motion estimation. To develop a fully functional assistive device, additional research on motion estimation is needed.

In addition to the artificial neural network, a closed-loop linear classifier method was used to transform EEG signals to an appropriate control command.[29] In the field of machine learning, a linear classifier identifies an object's characteristics by forming a classification decision using a linear combination of features. This technique works well for systems with multiple features (variables). Although accuracy is lower for linear classifiers compared to nonlinear classifiers, the computational speed of the former is much higher for training and testing. Looned et al. adopted this technique to identify five motion patterns: elbow extension, elbow flexion, wrist pronation, wrist supination, and hand open.[29] The system achieved an average classification accuracy of 98% from five volunteers during single task evaluation.

One limitation of machine learning controllers is the amount of data that are required to train the models. In order to derive an optimized model, many subjects and

data sets are needed. Tang et al. required 48 data sets to train their model for each of the 2-s, 4-s, and 8-s duration elbow motions. Each data set consisted of four EMG channels and one elbow angle channel of data, which were sampled at 1024 Hz. As a result, the training data consists of over 3.4 million data points that are needed to train the model. Even given this volume of training data, the neural networks still only achieved an average RMS error of $10.9°$ during control of their device. Neither Xiao et al. nor Looned et al. discussed how much data was used to train their models. This highlights the need for developers to both examine the accuracy–computational demand trade-off and provide these details within their research articles.

Biomechanical model control. Although non-physiological model-based control systems have better system response performance compared to other control strategies, their control accuracy is limited. To improve the performance of wearable assistive devices, Iqbal et al.,[59,60] and Taheri et al.[90] incorporated the dynamic model of human joints into their control systems. Although the control accuracy of such devices largely depends on the complexity of the model, the potential of these control methods has been recognized by the research community, and may likely become one of the common options for the control system design of wearable assistive devices. Since joint dynamics are the direct result of muscle activation and other biological phenomena together, such as joint friction, to control a wearable exoskeleton device, Ueda et al. investigated applying simplified muscle models together with a joint dynamic model using EMG input. This study proposed an individual muscle force control algorithm that aims to obtain a wider variety of muscle activity data.[20] This algorithm estimates the amount and direction of the force of the subject's hand by modeling nine joints from the torso to the wrist. Although the simulation and experimental validations have shown the validity of the proposed concept, future work is required to improve the control accuracy, to validate the efficacy, and to validate the system with dynamic tasks.

Empirical model control. A robust mechatronic system often uses a feedback control strategy. However, this does not necessarily mean that control systems without sensory feedback are obsolete in wearable assistive devices. The open-loop empirical process control uses a predefined model to associate the input signal to the output signal with no feedback. The application of such control systems is often for the purpose of initial testing, monitoring, evaluation, or low-end control. Sugar et al.,[16] Kazi et al.,[37] Higuma et al.,[36] Kang et al.,[63] Yun et al.,[77] Allotta et al.,[43,44] and Conti et al.[45] adopted open-loop empirical process control

in their studies. These are undoubtedly simple control strategies to use for a wearable assistive device. However, the lack of sensory feedback results in lower accuracy and reliability in general, compared to their closed-loop counterparts. Although such control methods are easy to implement and have a low relative cost, the increasing demand on smart technology forces research on wearable assistive devices to adopt smart feedback control strategies.

Other control strategies. In addition to the aforementioned control systems, Vaca Benitez et al. implemented a multi-input, single output model structure in a wearable elbow rehabilitation brace.[23] This model is based on system identification with a recursive least square (RLS) algorithm, which utilizes EMG, position and force signals from the user. The proposed system showed good performance in matching the user's real signals. However, the RLS algorithm reacted sensitively to the noise in the signals, especially the EMG signal. This is due to surface EMG signals containing a large portion of noise and muscle crosstalk. Although the proposed system presented promising results, it is crucial to improve the robustness of the algorithm to the noise residing in the sampled signals.

Kyrylova proposed a simplified neural activation model that estimates the muscle activities from two antagonistic muscle groups.[28] This model was integrated in a Kalman filter to generate the control signal for a wearable assistive device using EMG and joint position signals. With the help of the Kalman filter, the difference of neural activation from the two muscle groups can be mapped directly to the user's motion history, which allows the speed profile to be estimated one step ahead. The experimental validation with pre-recorded data showed very promising results, in terms of the overall control accuracy of the system. To validate the efficacy of the device, on-patient assessment is required in the future.

Thanks to the rapid growth of the computational capability of microcontrollers, the application of model-based control strategies in wearable assistive devices has increased considerably. Rocon et al. developed a three degree-of-freedom wearable orthosis for tremor suppression using a model-based controller, called the weighted-frequency Fourier linear combiner (WFLC).[19] Instead of modeling the musculoskeletal relations of the target joints and muscles, the WFLC adapts both the frequency and amplitude parameters of the Fourier series to the input signal. This method improved the response performance of the wearable assistive device, and the implementation of frequency estimation greatly improves the performance of the controller. However, the use of this pure sinusoidal model is insufficient to represent a real input signal.

Overall comments and future directions. Control systems function as the decision maker of wearable assistive devices, and play an important role in processing the measured signal from the sensing system and in regulating the actuation system. Control strategies, such as threshold control, PID control, linear classifiers, among others, are commonly implemented in wearable assistive devices. These control strategies do not require the embedded system to have high computational power, leaving the embedded system with enough processing time to perform other important tasks. This is an advantage that is especially important for devices that use physiological signals, such as EMG signals, since they often require multiple channels of data that are sampled at higher frequencies than those of voluntary motion. Since data sampling and processing occupy a large portion of the computational resources, the control accuracy of such devices may be limited.

The use of artificial intelligence-based and model-based control methods may result in better control accuracy than simpler control systems based on threshold or PID control, especially the ones that use physiological-based signals. To address the issue of high computational load of using these more advanced control systems, cloud computing could be a potential online solution, which is limited by the data transfer rates of the network. With the ultimate goal being real-time control of the device, the computational demands of the control system and limited computational resources available to these devices pose a major challenge.

Computation

Modern digital computer systems are the foundation for implementing a variety of aspects of sensing, actuation, and control of wearable assistive mechatronic devices. The complexity of these devices creates a large demand for processing, analysis, and storage of information, which is being supplied by computer systems and electronic components. Although, the computer systems facilitate the interaction of all of the mechatronic system components, some authors have neglected to include important details relating to the computer systems used in the design, development, and testing of their devices. From the review, no description of the computer architectures or systems was given for 21% of the devices.[20,27,33,37,38,42,48,50,55,62,64] Of the devices that provided computer system information, the general computer hardware and software specifications have been extracted, as follows.

Computer hardware. Computer system hardware is described in 79% of the reviewed devices, although

very briefly by some. The descriptions range from as vague as "a standard data acquisition board" to listing hardware components, their connections, and their communication protocols. General purpose computer systems, such as a laptop or personal computer, were listed as an integral component of the computer architecture in 32% of the devices,[16,17,21,24–26,28,29,34,35,40,41,52,54,59,60,65,66,68,72,73] while 34% of devices listed the use of off-the-shelf microcontroller boards.[11,36,41–43,47,49,53,56,63,65–67,70,72,76,77] Where model numbers are listed, basic processor information can be looked up, but only 11% of the devices listed basic processor and memory information.[18,22,28,29,35,65] To complement these computer systems, 26% of the devices are using other off-the-shelf electronics, such as data acquisition boards and sensing platforms.[17,19,24,26,28,34,35,39,40,52,57,59–61,68,72–74] In order to increase the portability of these devices, the computer systems must be embedded within the devices or stored on the user's body. This means that computer hardware analysis is important to ensure that the computational requirements can be factored in when designing these devices. A breakdown of the type of computer hardware systems is presented in Figure 6.

Computer software. In terms of computer system software, a similar trend can be seen towards researchers using off-the-shelf software systems. The review reveals that 51% of the studies reported the use of off-the-shelf software with MATLAB (25% of the devices),[16,19,23,26–28,32,41,46,48,52,55,65] including the Simulink tool kit,[26,63,65] and LabVIEW (15% of the devices)[21,25,26,35,40,51,54,57] being the most popular. Other software systems mentioned were OpenSim,[18] SolidWorks,[16,24,28,74,75] SimMechanics,[16,43–45] ControlDesk,[17] Emotiv Cognitiv Suite,[21] OpenSignals,[24,28] Presentation,[23] Datalog,[22] DAFUL,[36,46]
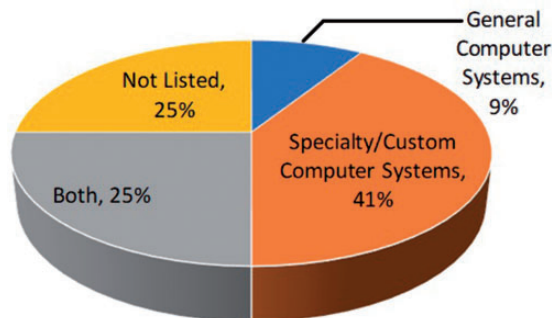
Figure 6. Distribution of computer hardware systems of wearable assistive devices. General computer systems include laptops, desktops and other personal computers, while the specialty/custom computer systems include microcontrollers, custom circuits, specialty computer systems, sensing electronics, and data acquisition boards.

FEMAP,[36] MPLAB,[65] BCI2000 Framework,[29,54] and XVR.[69] Although authors are listing their software systems, only 8% of the devices describe the operating system in which these software systems are executed.[22,28,35,41] The type of operating system that is used can have major effects on the execution of the control software and, therefore, should be reported. Programming languages, namely C and C++, were used in 9% of the devices as a primary development tool for software.[11,19,24,28,65] Very few descriptions of information regarding the software structure, complexity or timing can be found in the literature. Some of the software structure can be inferred from the control system descriptions, but it may not be possible to derive the entire software architecture from the control architecture, as they may not be mapped one-to-one.

Overall comments and future directions. One of the successes seen with the computer systems is in the required power supplies. Both lithium-ion[63,66] and lithium-polymer[18,67,77] batteries have been used to power the motors and the electronics of these devices, making it possible to increase portability. These power supplies remove one of the aspects that tether these devices to specific locations. However, much work still remains in reducing power consumption of the electronics, as well as decreasing the weight of the battery, while extending the amount of power provided. Power supplies are an important research area that supports the vision of these devices being used in a continuous all-day manner.

It is seen that many of the devices used desktop or laptop computer systems, off-the-shelf microcontrollers and other self-contained electronic systems for sensing or actuation, supporting the idea that developers are focusing on proof-of-concept development. This development strategy reduces the amount of time and resources needed to create a functioning prototype. By using off-the-shelf software systems, mechatronics engineers are able to prototype devices more rapidly.

The popularity of the Simulink tool for MATLAB and LabVIEW leans toward the view that engineers in this field may be more comfortable using visual-based control system development tools. It may also reflect the fact that many of these devices are still prototypes and, therefore, developers are choosing development tools that they find more effective for rapid prototype development. One potential limitation of using these tools is that the control software developed with them is often not able to be used in the final product. Existing embedded computer systems are likely to be unable to meet the processing requirements using software systems developed for desktop computer systems. These software systems will not typically operate on these embedded systems. In cases where it is possible

to execute them on embedded systems, the embedded systems do not have enough resources to complete the tasks required of wearable assistive devices in similar time periods as their desktop counterparts. As a result, the development periods and costs will be increased to account for the redevelopment of the control software in way that enables them to be executed appropriately on embedded computer systems. This limitation could be mitigated by using software development methods and tools that are appropriate for the final product from the beginning of their development projects. Reconfigurable computer hardware, such as field-programmable gate arrays, may also be a potential solution, but have yet to be implemented and reported by this research community.

Improvements to this research area can be made by development teams weighing in on what they consider important aspects of the software and hardware components that are required to replicate or evaluate results. The vagueness and lack of computer hardware and software details make it difficult to understand and reproduce the designs and experiments with wearable assistive devices. Even basic details of the computer systems, such as software versions, libraries, operating system software, model numbers of physical components, and processing resources, would help to mitigate this issue. One of the most important aspects for researchers and developers alike is to standardize information about the computer systems of these devices. If researchers are unable or unwilling to provide basic computational information, it hinders the evolution of this field. Many of the computer systems included in this review operate the device as expected because the computational environment has more resources than required. However, a limitation arises as the complexity of the computation grows, while the requirements for power and space on the devices or body limit the resources available in such embedded computer systems.
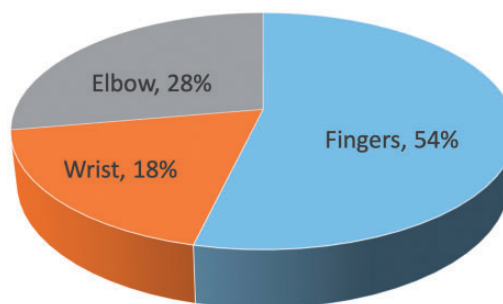
Applications

In this review, the applications of these wearable assistive devices are aimed at assistance with human motion. Categorization was made in terms of targeted body segment, purpose, and functionality. The targeted body segments were defined here as those to which assistance was actively applied, as opposed to passive assistance or support. The purpose of each device refers to the specific motivation behind the research and design, which is directed towards a musculoskeletal disease or clinical disorder that causes a known impairment. Functionality refers to the type of stimulus that the device is meant to provide to the wearer, such as assistive or resistive forces to the target joints, or

suppressive forces for involuntary motion. The review of these characteristics reveals trends about the application of these devices.

The targeted body segments were found to be divided into four main upper body sections: hand/fingers, wrist, elbow, and shoulder. Of the reviewed devices, 87% targeted a single body segment, such as one or more fingers, the wrist, and the elbow, while 13% were developed for multiple body segments. All multi-segment wearable assistive devices were developed such that the multiple targeted segments are directly connected in series. In total, three devices targeted the elbow and wrist,[19–21] two devices targeted the elbow and shoulder,[17,18] one device targeted the wrist and hand,[41] and one device was developed for the shoulder, elbow, and wrist.[16] Figure 7 gives a visual representation of the attention given to each joint by developers of the single-segment devices.

In terms of the purpose driving the design of these devices, there was no specific clinical disease forcing the constraints or requirements for each design. Instead, the overlying objective for these devices was the restoration of ADLs in impaired individuals. Nevertheless, clinical diseases and disorders were referenced in many of the introductory statements as a motivational explanation, the most common being stroke, which was referenced in 48% of the reviewed articles. Stroke was cited in most articles due to its prevalence. For instance, Burton et al. cited stroke as, "the single most common cause of severe disabilities in the developed world".[48]

The specified functionality of each device was found to be divided into musculoskeletal rehabilitation and tremor suppression. A review of rehabilitation modalities by Basteris et al. defined a rehabilitation device as one which can provide motion intention recognition and provide active assistive or resistive modalities depending on the patient's progress.[91] Since tremor is a ND that causes involuntary cyclic motion, the devices that are designed for this purpose require a different control architecture and performance constraints than

Figure 7. Distribution of devices with respect to the targeted body segment.

Figure 8. The normalized distribution of devices by targeted body segment and functionality. The main applications for these devices are to either suppress tremor or to assist with musculoskeletal disorders (MSDs).

rehabilitative devices. From the literature, 87% of devices were designed to rehabilitate MSDs, while 13% were designed to suppress involuntary tremor motion caused by NDs. Figure 8 shows the normalized distribution of rehabilitative and tremor suppressive devices for each body segment.

Overall comments and future directions. The results from the analysis of applications, as seen in Figures 7 and 8, indicate a strong trend toward rehabilitation devices in the finger and elbow joints. One reason for this result could be due to limitations in the capabilities of existing actuation technology. For example, to assist the shoulder joint during rehabilitation procedures, a larger actuator is required to produce motion of the arm. Not only would a large motor be heavier and larger, but the power consumption of the actuator would require larger power supplies to be carried by the person wearing the device. This is complicated further by the fact that the shoulder is a more complex joint and would require control of multiple degrees-of-freedom. Timmermans et al. concluded that recovery would be drastically improved if focus were equally placed on distal and proximal joints since ADLs require full mobility from every active joint.[92] Currently, there is no wearable assistive device that provides active assistance to the entire arm. Therefore, further research should continue the trend towards development of multi-segment devices that provide assistance from the shoulder down to the fingers.

Due to the complexity of humans and their motion, it is difficult to define requirements for a particular disease across all people. This lack of requirement makes it very challenging to design useful wearable assistive devices. Many devices examined in this review are still far from being ready for applications involving clinical testing.

Discussion

Developing mechatronic devices to assist with human motion has been an area of research interest for decades. However, improvements in technology have enabled an explosion in the development of assistive devices as wearable entities. In this review, 53 wearable assistive devices were examined to determine the state-of-the-art of the research and technologies driving their development. Five main areas, sensing, actuation, control, computation, and applications, were explored to identify trends and challenges surrounding the development of these devices. The following discussion will present the general trends in the field of wearable assistive devices, challenges facing each of the five key areas, and potential solutions to improve these research domains.

General trends

A major societal problem is supporting the research demand for wearable assistive devices. The number of disorders far out-weighs the resources available to assist with treating them or increasing the quality of life of individuals suffering from these disorders. When looking across the reviewed devices, 57% were developed and presented within the last five years. This shows that research efforts have more than doubled in this time period, despite a lack of clear requirements from clinicians.

The growth of wearable assistive devices is promising and creates a positive outlook for these devices as solutions to the growing MSD and ND problems. However, due to the newness of these devices, this area of research is still quite immature. Currently, only one commercially available upper-limb wearable assistive device, the MyoPro, is available for clinical use. Commercialization may be difficult as clinicians are hesitant to use tools that are not regulated, while government agencies are hesitant to regulate tools that are not used, proven to be safe, or more effective than traditional interventions. Furthermore, it is difficult to objectively measure functional improvements in human motion, which are major criteria desired by both clinicians and device regulators. Wearable assistive devices offer new opportunities to provide objective measurements of motion parameters, but the research connecting these measurements to patient outcomes is still limited.

Of the devices presented in the literature, a large amount of variation is seen among the technologies and methods used to support these devices. Exploration of technologies is expected with any emerging research area, but, in this case, it is likely due to the inability of technologies to fully meet the

engineering requirements. The novelty of these devices is also seen from the lack of comparative studies in the literature. The complexity of these devices and variability of humans makes comparison a difficult task. Adding the fact that none of the devices are available commercially, the challenge of duplicating experimental results and performing comparative studies is further increased.

One of the biggest challenges facing the field of wearable assistive devices is the lack of requirements, details, and standards in the literature. Many of the reviewed articles provide potential lists of disorders, or propose their device for general motion assistance. This shows that there is a lack of clear requirements being given to developers from medical professionals regarding assistance with any particular disorder. In this review, the inclusion criteria used was not overly strict, as it stated only that the researchers had to vaguely describe at least three of the four areas of sensing, actuation, control, and computation. As a result, many devices were not included in the review as the descriptions could not meet these criteria. Of the devices that were included, many of them had vague descriptions of these key areas, supporting a general lack of information crucial to the research community. The ability to understand, duplicate, compare, and improve upon existing research depends highly on the availability of this information and, therefore, is a hindrance on the evolution of this field.

Device evaluation and safety features were not discussed in general. In some cases, evaluation of engineering criteria is performed on sub-systems, but no integration or system-level testing was performed and presented. In other cases, system testing occurs, but only on a limited number of participants. Either case makes it difficult to generalize the performance of the system. Although safety features are typically seen as later-stage requirements, discussion of the potential features would assist in creating a positive image of these devices. These scenarios might be expected of devices that are still in the prototyping and early development stages. However, performance testing and safety features are vital for them to become regulated medical devices. The ability to persuade the community to adopt these devices relies heavily on the performance of the device to behave as intended and for their safety systems to ensure no further harm is done to the end-user as a result of their usage.

Sub-system challenges

Sensing systems, functioning as the feedback link of a wearable assistive device, play an important role in proper control system execution and user monitoring. Based on the review of the existing sensing systems, a number of common limitations were identified, which include a lack of sensor feedback, insufficient sensing modalities, and a lack of proper calibration procedures. A wearable assistive device with open-loop control does not require the use of sensors. However, the system performance of such a configuration is often complemented by the use of fixed-step actuators. Although the complexity of such configurations is minimized, the overall system accuracy is lower than systems with closed-loop control.

The human upper limb is a complex nonlinear system, which creates the design requirement for wearable assistive devices to involve multiple sensing modalities in order to achieve high control accuracy. However, only 40% of systems used multiple sensing modalities. One reason could be that increasing the number of sensing modalities increases the computational demand, cost, and system complexity. Although the performance of a system with a single sensing modality can be complemented by better control strategies, such limitations still require greater consideration from researchers for the future development of a wearable assistive device.

Lastly, sensor calibration is often the first step for validating devices on humans. Due to individual differences, the sensing system should be calibrated individually to achieve optimal performance. For a device with many sensors, calibration of the sensors may be costly. However, the potential impact of not calibrating the system includes compromised system performance, system failure, and even risks for the user's safety. As a result, maximizing adoption of the device must consider the trade-off between the cost and the performance related to calibration. In this review, the majority of the systems did not detail the sensor calibration process. Including this information in the dissemination of future studies will help to increase device adoption through an analysis of the trade-off between factors related to sensing systems and calibration.

Actuation systems are important to enable the interaction between the wearable assistive device and the human. Through the analysis of the literature, it was found that DC motors and pneumatic actuators are the most commonly used actuators. However, these actuation technologies are not meeting the needs of wearable assistive devices, as the size, weight, and power consumption of the actuators limit the application of the devices. As a result, there are new types of actuators being tested and developed.

In addition, some actuators used in the existing devices were not justified as to their usage over alternative actuators. Information, such as mechanical design, user interface, or safety considerations, which play a crucial role in actuation selection, were not always included. The lack of these considerations could result in a

lengthy iterative design process in order to determine the appropriate actuator and limit the number of commercially available wearable assistive devices.

The control system functions as a behavior regulator of wearable assistive devices. In this review, it has been identified that many of the control systems used in wearable assistive systems employ simple control methods. The prevalence of simplistic binary-based control methods, such as a threshold controller, is useful for prototyping, can reduce system costs, and may be suitable for certain applications that rely on abilities of the user. However, these control methods do not account for the complexity of the human motor control system and may not be able to adapt to changes in the user, the motion task, or the environment. As a result, the simpler control methods may not be viable for many applications that involve users with limited cognitive or physical abilities. Although complex control models do exist, their application in wearable assistive devices may be limited by the available computational resources. Controller complexity also increases overall cost and may present a greater chance for errors to occur. In developed cities, cloud computing could be an alternative solution to the computational limitations, but the availability of network resources may provide a different set of limitations, especially in remote areas or cities with limited resources.

The majority of computer systems for these wearable assistive devices are implemented on desktop or laptop computer systems. Using these computer systems provides platforms that enable faster proof-of-concept designs and rapid prototyping. However, the transition to embedded computer systems may result in lower computational performance, due to the trade-off between computational resources and other requirements, such as power supplies, electronic components, or size requirements.

Currently, no device exists to assist the entire upper limb. This could be partially due to the aforementioned challenges with actuation technology, power consumption, and computational resources, as well as the novelty of this research domain. However, there are many rehabilitation activities whose focus is on single-segment therapy and do not require whole-arm assistive systems. Both types of devices have their usefulness, but require input from application domain experts for their benefits to be maximized. Mapping the devices as solutions to particular applications requires the specification of clinical requirements and this crucial information is missing from much of the literature. As a result, the existing devices have, and will continue to have, a strong bias towards fulfilling engineering characteristics until clinical characteristics become available.

Opportunities for advancement

Many of the successes and challenges highlighted in this review are simply a consequence of the current state of the research fields surrounding wearable assistive devices. Given more time and continued efforts, improvements are likely to evolve without much intervention. The interest and existing research activities afford a promising future. However, the authors have identified two major strategies that can be used to accelerate the evolution of these fields.

First, standardization of research, clinical, and engineering information would help development and regulation of these devices. Research efforts could be better directed and informed if standards for reporting on wearable assistive devices were created. As seen in this review, many of the research articles do not provide information sets that are complete enough to enable duplication of results or allow for detailed comparison of existing devices. Page limitations set by publishers in the fields surrounding mechatronic devices could be causing this issue. Providing a reporting standard could allow for new article formats from publishers, specific to these research areas, and enable the community to access the details required to disseminate the research. Another area of possible standardization would be regarding the requirements for MSDs and NDs. Characteristics of these disorders may vary between patients, but the fact that disorders can be identified and classified, means there are common properties. Working with medical professionals, developers could generate sets of requirements, for each disorder, that enable more focused research efforts. The last area for potential standardization is within the evaluation and testing of wearable assistive devices. Currently, no testing standards or templates exist, even for engineering metrics. Testing protocols need to be customized based on many factors, but some guidelines or general processes are of great importance to the evolution of this research domain. Furthermore, small sample sizes and poor statistical analyses make it difficult to generalize conclusions from the findings or compare across these studies. Providing a base set of evaluation tools for the community would help to alleviate this problem.

Second, promotion and further development of a multidisciplinary culture is required to develop wearable assistive devices and realize their social benefit. The complexity of these devices, their components, and the end-user requires experts from many engineering domains to build systems that meet functional requirements. Although the engineering fields have shown great progress, the existing devices may never be integrated into clinical practices if input from other stakeholders, such as government regulation agencies,

clinicians, industry representatives, researchers, and end-users, are not included into the development processes. Methods for producing solutions to complex multidisciplinary problems, such as the development of wearable assistive devices, already exist in other domains. For example, software engineering has proposed and shown the value of development processes, which include non-engineering stakeholders. Involving more views into the design process requires more resources, but helps ensure that each device provides the maximum benefit for its intended purpose of assisting with human motion.

Conclusion

This article presented a thorough review of the literature related to wearable and assistive mechatronic devices for upper limb rehabilitation. Although only one device is commercially available, many devices have been developed and tested by the research community. The review of 53 wearable assistive upper-limb mechatronic devices shows a variety of solutions being explored as part of their sensing systems, actuation systems, control systems, and computer hardware and software. In general, devices are still far from being applied in clinical tests in a way that will provide useful and consistent patient care. Further progress into all of these areas is needed in order to improve portability, responsiveness, comfort, and safety.

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