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SOFT ROBOTICS (M SPENKO, SECTION EDITOR)

Human Assistance and Augmentation with Wearable Soft Robotics: a Literature Review and Perspectives

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Abstract

Purpose of Review Wearable soft robotics has demonstrated many unique capabilities in human assistance and augmentation. This paper discusses the recent trends and remaining challenges in designing soft actuators, soft sensors, and controllers for wearable soft robots.

Recent Findings Different actuation mechanisms for wearable systems were investigated in this review. We include a synopsis on the design of soft sensors and algorithms for sensor fusion and discuss the recent trends for sensing simultaneous deformations and implementing machine learning techniques for soft sensor fusion. We also present a discussion on layered controller design and the evaluation metrics for experiments with healthy and impaired subjects.

Summary We review three commonly used soft actuation mechanisms and provide their characteristics, in which the balance between material stiffness and functionality is still a challenge. We present the advances in soft sensor design and discuss the challenges in fusion algorithms for wearable soft sensors, such as inter-subject adaptability and sensor location movement. We also discuss the model-based and model-free controller design together with the evaluation criteria for healthy and impaired users, in which autonomous operation for personalized assistance is still an open challenge for controller design.

Keywords Wearable robotics · Soft robotics · Human-robot interaction · Rehabilitation

Introduction

Wearable robots are advanced human symbiotic robotic systems characterized by suitable shape, kinematic, and weight factors to be worn on the human body with the function of either augmenting and assisting or restoring human limb function [5, 6]. Over the past decades, wearable robots have been applied to facilitate neuro-rehabilitation [7], prevent work-related injuries [8], enhance the performance of sports training [9], and augment human capabilities in labor-intensive tasks [10]. For example, there are approximately 6.6 million stroke patients in the USA, and at least 65% of them suffering from gait impairment [11]. Wearable robotics provides a promising solution to meet this increase demand for physical therapy and enable in-home rehabilitation [12].

Currently the actuators, sensors, transmission, and braces of wearable robots are mostly made of rigid materials. Rigid exoskeletons are often composed of heavy motors and bulky structures that could cause fatigue to the users and restrict their natural motions. Furthermore, rigid wearable robots require precise mounting and adjustment for users, and any misalignment with the human joint can jeopardize the robot performance and even pose safety risks to the users [13].

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To address these challenges, there has been a growing interest in introducing soft materials (e.g., silicone and textiles) into wearable sensors and actuators [14]. Fluids, cables, and shape-memory-alloy actuators are among the most popular actuation mechanisms [15, 16]. In the meantime, soft sensors have been designed to measure strains and curvatures of the soft robots using flexible electronics, liquid metals, optical fibers [17–19]. Wearable soft robots have demonstrated many advantages over their rigid counterparts, as they are generally inexpensive to make, safe to use, lightweight, highly customizable, and able to generate versatile motion profiles [20]. As a result, research in the field of wearable soft robotics has been fast expanding in the past decade and has become a highly prominent subtopic in the wearable robotics field. Examining the quantity of published research articles in the overall wearable robotics field reveals that 27% of them are about soft robots in 2010 and it increased to 41% in 2020.

Wearable soft robotics is a highly interdisciplinary research topic which requires integration of knowledge from material science, solid and fluid mechanics, mechanical design and manufacturing, modeling and control, human systems engineering, to name a few. Wearable soft robots have been integrated with human users as exosuits to assist various human joints [21], robot manipulators to augment human capabilities [2], and haptic devices to provide cues and feedback to the users [22]. While earlier work in wearable soft robots focused on identifying the appropriate materials and actuation mechanisms [23], a large number of recent research in wearable soft robots focus on integrating these robots with human users by developing novel soft sensors [24], designing autonomous control algorithms for the soft robots [25], and conducting tests with healthy and impaired users [26, 27]. A few wearable soft robots have been productized to make these new technologies available to the public [28–30].

This article will review the recent trends in design, sensing and control of wearable soft robots, which supplements and extends several recent review papers on textile-based wearable robots [31], rehabilitation robots powered by pneumatic muscles [32], machine learning methods in soft robotics [33], and control strategies for soft continuum robotic manipulators [34]. This paper attempts to present a holistic view of different aspects required to integrate wearable soft robots with human users, which include actuation mechanisms to drive wearable soft robots, designs and algorithms of soft sensors, controller syntheses for wearable soft robots to autonomously collaborate with human users, and human evaluation results. Finally, we will also present some remaining challenges and future directions in different aspects of wearable soft robots to successfully deploy them into daily lives of the human users.

Design of Wearable Soft Robots

Wearable robotics can be used for rehabilitation, assistance, and augmentation. In this paper, we divide wearable soft robots into four categories according to their primary functions: *exosuits*, *manipulators*, *haptic devices* and *sensing suits*. A soft robotic exosuit is often a robotic garment that can apply forces and/or torques to human joints. A soft manipulator can act as an extra arm [2] or finger [38], which can extend capabilities for healthy users or become a prosthesis for impaired users. Soft haptic devices are designed to provide humans with direction cues, motion guidance and realistic feedback with virtual objects or teleportation with less harm and larger range of adjust ability compared to rigid ones [22]. Sensing suits are designed for measuring human motion. Most wearable soft devices are mounted on the users through fabrics and velcros. The mounting mechanism ensures that the device can deform with the joint motion while staying relatively fixed to the body. Some examples of wearable soft robot designs are presented in Figs. 1, 2 and 3. Primary functional requirements for designing wearable soft robots include output force/torque capacity, range of motion, user comfort, and safety. All these characteristics are highly dependent on the actuation mechanisms. In the section, we will review three most popular approaches in the literature: fluid-driven, cable-driven, and shape-memory alloy actuators.

Fluid-Driven Actuators

Fluidic actuators are widely used in wearable soft devices because of their compliance, simple structure, and wide range of force capability (Fig. 1a). The outputs of fluidic actuators are generated through deforming a sealed chamber (made of elastomers or fabrics) by pneumatic or hydraulic pressures. The peripherals of the devices (e.g., pumps, regulators, and tubes) are usually offboard. Recently, portable pneumatic sources are developed and users are able to carry it on waist or back (Fig. 1c) [3]. Elastomer actuators have been applied in exosuits for shoulder (Fig. 1d) [4, 39] and elbow assist [40] as well as ankle rehabilitation [41]. They also widely used in other wearable devices such as assistive gloves [42, 43], wearable manipulators (Fig. 1b) [44, 45], and haptic devices [22, 46]. Most of the elastomer actuators are made of silicone or rubber with an inflatable chamber inside. Mechanical constraints such as inextensible layers have been introduced in the actuator design to generate different motion patterns upon inflation, such as bending, twisting, or elongation [1]. The inherent stiffness of elastomers is enough to support the device's structure, but it also makes these actuators relatively bulky and heavy for wearable applications.

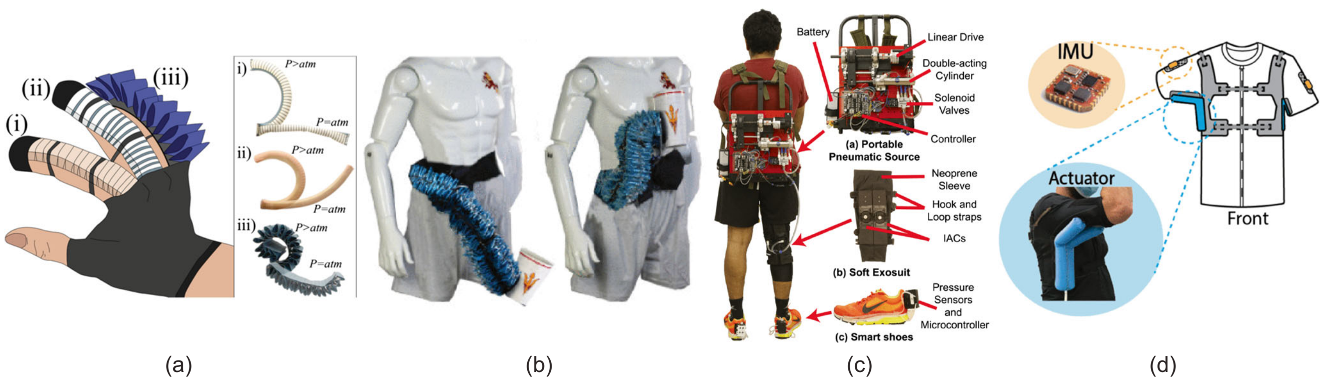

Fig. 1 Examples of fluid-driven actuators: **a** Elastomer, knitted fabric, and woven fabric fluid-actuators [1]. **b** Wearable soft manipulator made of the woven fabric actuator (©[2019] IEEE. Reprinted, with permission, from [2]). **c** Pneumatic actuators for a knee exosuit (©[2020] IEEE. Reprinted, with permission, from [3]). **d** Pneumatic actuators for shoulder assistance (©[2021] IEEE. Reprinted, with permission, from [4])

To mitigate this issue, researchers have introduced textile actuators that can fully collapse when deflated for assistive gloves [47], knee exosuits [48], and wearable manipulators [2, 49]. Fabrics are the most popular material for this type of actuators, including non-stretchable woven fabrics and stretchable knitted fabrics. Non-leaking materials such as thermoplastic polyurethane are often used to form fabric actuator's air chamber by heat sealing. Those materials are either coated on fabrics or separated as a chamber inside a fabric pouch. Since fabric pneumatic actuators can support higher pressure with thin walls compared to their elastomer counterparts, the device is much lighter with similar force/torque outputs, but it loses the capability to support structure with minimal inherent material stiffness. For instance, by evolving from elastomer actuators [45] to fabric actuators [2] for a three-segment soft robotic manipulator, the weight of the robot decreased from 1.6 to 1 kg and its payload capacity increased from 0.96 to 1.5 kg. Fluidic actuators have a systematic manufacturing process, can conform to different objects and can generate a wide range of forces and motion patterns. However, typical pneumatic actuators generally take seconds to inflate and deflate, making it challenging to assist human users in fast and highly dynamic tasks.

Cable-Driven Actuators

To achieve fast reaction, low inertia, and avoid bulky structure near moving joints, cable-driven actuators are utilized in wearable soft robots (Fig. 2a). Originally employed in many exoskeletons, cable-driven actuators move a joint by pulling cables across it with electric motors located away from the joint. In wearable soft robots, soft materials such as fabrics or elastomers are used as anchor points for cables across a joint. These actuators have been applied to assistive gloves (Fig. 2d) [37, 53], wearable extra finger [38] and haptic glove [54]. They have also been used in exosuits for the shoulder [55], elbow (Fig. 2b) [35], ankle (Fig. 2c) [36] and hip [56]. These devices utilize Bowden cables, which can transmit force or energy by the movement of an inner cable relative to a hollow outer flexible cable, to guide tendons around the body. In [36], a cable-driven soft exosuit was designed to assist walking. Components of the wearable brace on both legs weigh only about 1.0 kg, but the total

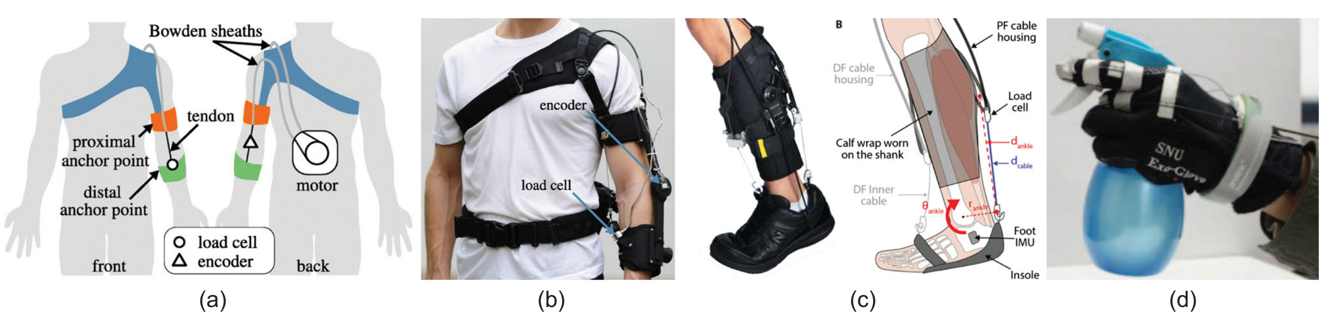

Fig. 2 Examples of cable-driven actuators: (**a**) and (**b**) Cable-driven soft actuators and a soft wearable device to assist elbow motion [35]. (**c**) A cable-driven soft exosuit for ankle walking assistance (©[2018] IEEE. Reprinted, with permission, from [36]). (**d**) A cable-driven assistive glove (©[2015] IEEE. Reprinted, with permission, from [37])

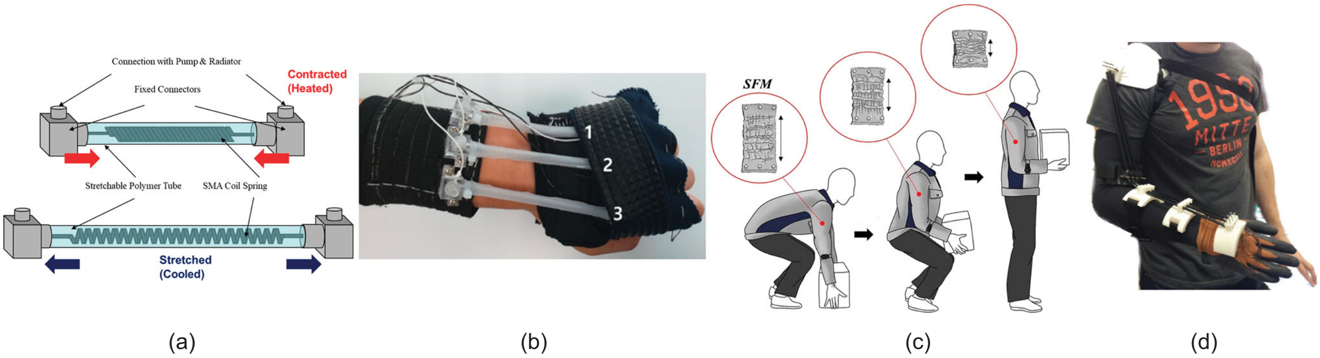

Fig. 3 Examples of shape-memory alloy actuators: **a**, **b** Shape-memory alloy actuators and a wearable robot that can assist wrist motion [50]. **c** Shape-memory alloy actuators for forearm force enhancement [51]. **d** An elbow exoskeleton driven by a shape-memory alloy actuator [52]

system including motors and power source weighs 3.8 kg. The system can generate forces up to 300 N at the ankle, at walking speeds up to 1.4 m/s. Cable-driven soft actuators can assist fast movement and achieve highly repeatable and bidirectional motion across a joint, but their mechanisms can be complicated to manufacture and the high friction of Bowden cable lowers the system efficiency [57].

Shape-Memory Alloy Actuators

Because of the need for silent and lightweight compliant actuators with large force capability, shape-memory alloy actuators have been developed for wearable soft robots (Fig. 3a). Shape-memory alloy actuators generate force through crystal phase change caused by changes of temperature or a magnetic field applied to them. They can be trained to memorize its shape at high temperature and could be deformed and return to that shape when heated. A two-way shape-memory alloy can also memorize its shape at low temperature as well. Such actuators are used in assistive gloves [58] and haptic devices [59], as well as exosuits for assisting the muscular strength on the forearm (Fig. 3c) [51] and wrist motion (Fig. 3b) [50]. A wearable robot that can assist the muscular strength of the forearm in [51] used shape-memory-alloy-based fabric muscles as actuators. It has shape-memory-alloy spring connected in parallel and wrapped with fabric with thread stitch to insulate the springs (Fig. 3c). One shape-memory-alloy-based fabric muscle unit weights only 24 g and can exert a force of 100 N with an input power of 150 W and helps to lift up to 4 kg barbell to the target position. Shape memory alloy actuators are lightweight, compact, and could be driven directly through electric power. However, the heating and cooling time before deformation is long, as it takes seconds to heat up and cool down. Without an active cooling system, the cooling time can be even longer [60].

Sensing in Wearable Soft Robots

Sensing in wearable robotics is vital to obtain crucial information about the users, actuator states, and the environments. Existing wearable sensors, such as inertial measurements units (IMU), goniometers, load cells, and strain gauges, have been integrated with rigid exoskeletons. However, these rigid sensors are often incompatible with soft robots as they compromise the inherent compliance and safety, and also lead to misalignment. This motivates the design of soft and flexible sensors that can be seamlessly integrated with wearable soft robots. This section will discuss the recent development in wearable soft sensor design and fusion algorithms.

Design of Soft Sensors

The design of soft sensors aims to achieve the sensing capabilities found in biological systems [67]. Wearable soft sensors are capable of measuring strain, force, curvature, joint angle and a combination of these properties through multimodal sensing. An overview of soft sensor designs can be observed in Fig. 4.

Strain Sensing Common principles employed to measure strain include liquid eutectic gallium-indium (eGaIn) [65], biphasic gallium-indium alloy (bGaIn) [68], aqueous ionic solution [18], ionic conductive liquid [69, 70], capacitive sensing [71] and polymer optical fiber (POF) threads [72]. Soft strain sensors commonly consist of a conductive material incorporated into stretchable supporting materials such as silicone elastomers [73]. The conductive filling serves as the active sensing material that responds to the strain of the encasing. When the microchannels filled with liquid conductive materials are deformed by stretching, the electrical resistance of the microchannels increases due to

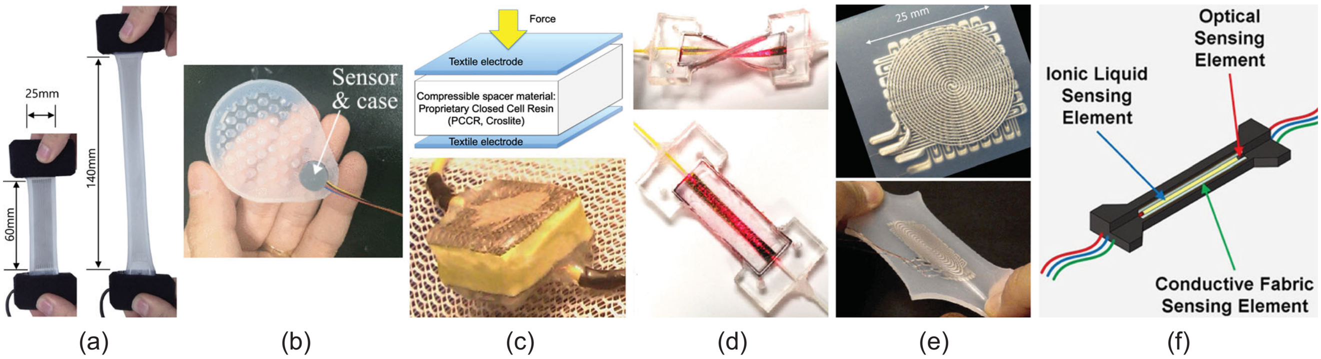

Fig. 4 Examples of wearable soft sensor designs: **a** eGaIn strain sensor (©[2019] IEEE. Reprinted, with permission, from [61••]). **b** Pneumatic force sensor (©[2018] IEEE. Reprinted, with permission, from [62•]. **c** Conductive textile capacitive force sensor (©[2010] IEEE. Reprinted, with permission, from [63]. **d** Polymer optical fiber strain and pressure sensor (©[2018] IEEE. Reprinted, with permission, from [64]). **e** eGaIn multimode strain and force sensor (©[2012] IEEE. Reprinted, with permission, from [65]). **f** Multimode multifunctional sensor consisting of ionic liquid, conductive fabric and optical element for bend, force and strain sensing (From [66••]. Reprinted with permission from AAAS)

reduced cross-sectional area, increased channel length, or both [18, 65, 69]. Recently, bGaIn was developed with improved stable conductivity over large strains and extreme stretchability, compared to the commonly used eGaIn [68].

Sensing strain with soft capacitive sensors is usually achieved by stacking flat or concentric layers of conductive plates with inter-layers of silicone elastomer, such that when undergoing strain the distance between the conductive plates changes and induces a change in the capacitance measurement [70, 71]. The conductive layers can be composed of ionically conductive fluid [70] or solid metal plates such as aluminum and silver [71]. In [72], the POF was utilized as a light-guiding thread for strain sensing. In POF strain sensors the intensity of the transmitted light drops along the length of the fiber. As the sensor is stretched the length of the sensor changes which induces a change in the light intensity.

Soft strain sensors usually demonstrate hyperelastic characteristics, with some studies reporting stretching twice their original length [18]. However, the viscoelasticity of the material has been shown to create hysteresis in dynamic stretching [74]. Two independent studies reported a maximum hysteresis of 26.45% [75] and 21.34% [76] of the respective sensor measuring resistance. Furthermore, some have reported drift in the sensor measurements over time and as a transient response to fixed strain conditions [71, 74]. Overall, capacitance strain sensors exhibit lower hysteresis and faster response times compared to resistance sensors [73, 77].

Force Sensing To measure force, common mechanisms employed in soft sensors include pneumatic chambers [62•], liquid eGaIn [78, 79], conductive textiles [63, 80], carbon fiber composite [81, 82], and POF [19].

Pneumatic chamber soft sensors consist of sealed airtight chambers that demonstrate a change in internal pressure to applied loads and are commonly manufactured from elastomeric materials or heat-sealable thermoplastic polyurethane [62•], similar to Fig. 4b. In dynamic loading, the viscoelastic characteristics influence the measurements and cause hysteresis [83], which implies that the dynamic characteristics of the air bladder cannot be neglected [84]. A hyperelastic pressure transducer was fabricated by embedding silicone rubber with microchannels of conductive liquid eGaIn [78]. Pressing the surface of the elastomer with pressure loads deform the cross-section of the underlying channels and changes their electric resistance. Circular patterned microchannels with eGaIn allow sensing surface pressure and exhibit insensitiveness to strains along any axis [65]. Multi-axis force sensing was achieved in [79] by arranging three star-patterned microchannels filled with liquid eGaIn.

Force sensing with conductive fabrics is achieved by stacking two conductive layers with an inter-layer of a compressible spacer material such that when the sensor is compressed the distance between the layers change and the capacitance measured between the conductive fabric also changes [63] (see Fig. 4c). Carbon fiber composites can be used as a conductive structure material that exhibits changes in electrical resistance when the structure geometry undergoes deformation. In [81], tensile loads of the sensor induce changes in electrical resistance between the carbon fiber composite structures as the layers of the U-shaped sensor design were deformed closer together or further apart. Multi-axis force sensing was performed with a set of carbon fiber composite conductors in the shape of a meander and positioned radially, such that forces on the sensor change the electrical resistance between the carbon fiber structures [82]. The POF was used in [19] for detection of insole contact forces. When the POF sensor is pressed, the sensor bends and induces a variation in the refractive index due to deformation of the fiber and stress-optic effect leading to a change in the light intensity [19].

Curvature and Angle Sensing Common principles to measure curvature include resistive flex sensors [17], liquid eGaIn [85, 86], and POF. Curvature resistive flex sensor designs consist of electrically conductive materials embedded within a flexible substrate [17]. When undergoing bending the substrate causes a mechanical stress of the conductive pattern that leads to a change in its electrical resistance. Curvature sensing with liquid eGaIn can be achieved by stacking two layers interconnected through the edges and a middle strut that induces compression loads on the liquid microchannel when the sensor is bent [85]. Furthermore, when this design is embedded with a serpentine pattern microchannel simultaneous sensing of curvature and strain is possible [86]. Resistive flex sensors are commercially available, although they exhibit drift in the sensor measurements over time, even in mechanically stationary conditions [17].

Soft sensor designs employing wearable inductive coils [87], POF [19] and piezoresistive sensors [88] have shown the capability to measure the relative angle between segments. Wearable inductive coils were implemented in [87] to measure the relative angle between two segments. Relying on Faradays Law of Induction, wearable wraparound coils were designed to transmit and receive the signal from one another through inductance. As the relative angle between the coils changes, the transmission coefficient will change due to misalignment of the coils. This property allows for a sensing principle that directly reacts to the joint angle state. In [88], a piezoresistive hinge sensor was fabricated which during bending the carbon particles are pulled apart or closer changing the sensor's resistance. Inductance-based sensors have reported robustness to variation in human tissue dielectric properties [87] and immunity to electromagnetic interference [89].

Multimodal Sensing Recent work has introduced single sensor designs to simultaneously sense multiple deformation modes [65, 66••, 90]. An early work [65] achieved sensing vertical force, and strain in two directions, by stacking two strain sensor layers and one force sensor layers with microchannels filled with liquid eGaIn (see Fig. 4e). A POF was used in [90] to measure twisting and bending. In [66••] (Fig. 4f) ionic liquid, conductive fabric and optical sensing elements were integrated into a single sensor design to allow sensing and decoupling combined deformation modes of stretching, bending and compression.

Algorithms for Soft Sensor Fusion

Fusion algorithms in soft sensors allow compensating limitations in individual sensors and improve the overall measurement accuracy. Kalman Filter (KF) [91–93], Multiplicative Extended Kalman Filter (MEKF) [94•] and machine learning techniques [61••, 95, 96] have been implemented to fuse readings from soft sensors and other sensing approaches. In [91], a KF was implemented to fuse soft resistive flex sensors with two infrared cameras to improve the accuracy and reliability of fingertip position tracking when occlusion is encountered in the camera system. The KF was also implemented with soft resistance-based textiles [92] and POF curvature sensors [93] for fusion with IMU data to improve knee joint angle estimation. This work was extended to quaternion-based MEKF, which showed further improved accuracy and repeatability for knee joint angle estimation in the sagittal plane [94•]. Compared to the KF, MEKF has demonstrated improved estimation results since it is applicable to non-linear dynamic systems. A limitation for both fusion methods in wearable applications is that obtaining a model of the human joint dynamics is often challenging.

To overcome this limitation, machine learning methods have been implemented to fuse sensor information without requiring a precise model of the human body dynamics [61••, 95–97]. A long short-term memory (LSTM) model was employed in [98] to fuse multiple soft strain sensors distributed through the human body for reconstruction of the 3D motion of the upper body. LSTM is a deep learning method effective for capturing long-term temporal dependencies [99]. A semi-supervised deep learning architecture was proposed in [100], consisting of a sequential encoder network, an alignment network, and a motion representation network, to estimate 3D position of the lower limb joints based on information from two soft strain sensors. Artificial Neural Networks (ANN) were employed in multimodal soft sensors to identify combined deformations of stretching, bending and compression [66••]. ANN [101], fuzzy logic [84, 102], and segmental regression approach based on a hidden logistic process (RHLP) [103] have been implemented to estimate the gait phases upon GCF measured from the soft force sensors.

Machine learning methods have demonstrated successful fusion of different sensors without requiring knowledge of the sensor dynamics. However, they require a considerable amount of data to train the models. For example, 1000 cycles of sensor stretching were required to build the training data set for one sensor [98]. In many wearable applications, a machine learning model has to be retrained for each human subject since the anthropometric information significantly affects the training data. This can be inconvenient for the users. In addition, wearable soft sensors can slide over the human body with human movement, which may invalidate the learned model and require frequent modeling retraining.

Control of Wearable Soft Robots

Wearable soft robots are often controlled in a layered structure. The outer-layer or high-level controller uses the sensor feedback of muscle activities, forces/torques, and/or kinematics to estimate the states and intents of the users and generate force/torque or motion references for the actuator. The inner-layer or low-level controller is designed to track the references, and the design of the low-level controller heavily depends on the actuation mechanism. A comparison of control strategies is shown in Table 1 and controller evaluation with human subjects will be presented in Section 2.

High-Level Controller

The most straightforward high-level controller is the classical finite-state machine (FSM) which maps the sensor measurements to a set of pre-defined reference trajectories. One early work using this approach in a wearable soft device was presented in [104•]. A three-state (grasp, release, and hold) FSM was designed for a soft robotic glove and the system provided constant assistance in each state. This work was extended to a four-state (relax, extension, pinch flexion, and power flexion) controller for a new soft hand with flex sensors placed on each finger and force sensors attached to the palm and fingertips [115]. In [119], a gait event based control system was designed to assist the hip flexion from pre-swing to terminal swing. The gait phases were identified through the insole sensor measurements under both feet and constant DC voltage was supplied to the system to assist hip flexion.

To provide more personalized and adaptive assistance, FSM have been combined with either human-model-based or learning-based approaches [25, 105, 106••, 120–123]. The new approaches still divide a task into several states but the trajectory in each state was generated through the biomechanical models of the human joints or machine learning models. In [105], the controller classified a gait cycle into two phases: stance and swing, and then the desired torque profile was calculated based on the identified human quasi-stiffness and damping model of the knee joint for the swing phase only. During the stance phase, the controller was designed to provide zero assistance. In [122], a two-state (bending and grasping) controller was proposed for a pneumatic artificial muscle based soft glove. The controller switched between the bending mode and grasping mode based on the local sensor measurement. The position mode utilized ANN to map from the bending angle to the desired pressure while the force mode utilized the mathematical model which was based on the theory of conservation of energy to calculate the desired pressure. The main advantage of the classic FSM and its variations comes from the simple structure and implementation. This feature also makes the FSM approach very popular in both rigid and soft robots [124]. However, it requires careful tuning to account for the variations between different subjects [125].

To overcome the limitations of the FSM method, many controllers have emerged by using human models [109–111, 126, 127]. These controllers utilized the biomechanical models of human joints to estimate the joint torque and then calculate the desired force/position profile for the actuators. In [110••], the controller was designed to assist squat (i.e., knee bent and back straight) and stoop (i.e., knee straight and back bent) lifting. The desired assistive force was calculated using a simplified bending model of the transition region between the lumbar spine and sacral spine in the lower back. In [126], a controller was designed to assist grasping and flexion/extension of the elbow joint utilizing a simplified human arm dynamic model. The simplified model utilized the measurements including the mass and length of the forearm and the elbow's angular kinematic information to calculate the desired assistive torque profile. An admittance controller was applied to map such a torque profile to the desired angular position of the actuator. In [127], a surface Electromyography (sEMG) driven musculoskeletal model based controller was utilized to assist the elbow flexion and extension. The elbow flexion-extension torque was generated from three sEMG channels and the elbow bending angle. The sEMG measurements were converted to activation-dynamic components through a muscle twitch model. The activation-dynamic components were mapped to seven muscle-tendon units and the desired assistive torque was calculated accordingly.

Compared with the FSM method, the human-model-based controllers provide more natural and personalized assistance profile. However, these controllers are usually built on simplified human models such as static models [110••] or second-order dynamic models [126, 127], and the modeling uncertainties can significantly degrade the controller performance. To mitigate the uncertainties from the simplified human model, machine learning becomes increasingly popular for the high-level controller design. In [112], a deep learning algorithm was applied to the pneumatic-driven soft glove. The pressure measurements and the glove position were used as the input-output pair to train the model and an open-loop control was applied to drive the soft glove to the desired position. In [113], a Vision-based Intention Detection network from an Egocentric view (VIDEO-Net) framework was

Table 1 Comparison of control strategies

	Controllers	Advantages	Disadvantages	Evaluation criteria
High-level	FSM[104•–107••]	– simple structure and implementation	– require fine tuning to work across different subjects	– sEMG signal of the target muscle groups – functional scores in clinical tests – metabolic cost
	Human-model-based [26, 108–111]	– provide natural and customized assistance profile	– simplified human dynamics and modeling uncertainties degrade the controller performance	
	Machine learning [112–114•]	– adaptive to different users and tasks without requiring human models	– requires large data to capture the nonlinear dynamics – convergence proofs are challenging	
Low-level	PID [26, 107••, 110••, 115]	– simple control structure – no need to identify the soft actuator dynamics	– requires developer experience on parameter tuning	– tracking error of desired air pressure – tracking error of desired cable lengtht – tracking error of desired driving voltage
	MPC [116]	– controller can be proactive without violating safety constraints or causing actuator saturation	– requires accurate model description – computational cost is high	
	SMC [117, 118]	– robust to modeling uncertainties and disturbances	– conservative actions and high control gains	

proposed to predict the grasping intention. The VIDEO-Net framework utilized user arm behaviors and hand object interactions through obtained visual information to detect user intentions. The learning-based method provides an alternative solution when the analytical or empirical model of human joint is difficult to obtain and it shows reliable results in known environments. However, it also requires a large data set to capture the dynamics of the system and the convergence proof is difficult to establish [34].

Low-Level Controller

Once the desired trajectory is generated, a low-level controller will be tasked to track the reference. The proportional–integral–derivative (PID) controller is the most commonly used method for wearable soft robots [26, 107••]. In [110••], a simple PID controller was applied to a cable-driven soft exoskeleton for stoop lifting assistance. The controller was designed to drive the motor to the desired velocity. Similarly, a PID controller was designed based on the flow dynamics of the compressed air to drive the pneumatic soft glove to the desired air pressure [115]. The PID controller has a simple structure but the tuning of PID control parameters can be challenging and time-consuming.

As an alternative approach, researchers have also looked into model-based controller design. In [116], a model predictive control (MPC) method was presented for a cable-driven system to track the desired torque profile. Four state variables: angular positions and velocities of the motor and the human knee joint and three outputs: angular position and velocity of the knee joint and assistive torque were used to describe the state-space model. The MPC method ensures that the system will satisfy the constraints on range of motion and assistive force/torque. However, an accurate actuator model is required for the MPC method but it is challenging to build such models for soft actuators. In addition, the computational cost for running the MPC is usually high.

To address the modeling uncertainties, robust control method also starts to emerge. In [117], a sliding mode control (SMC) was applied to a soft pneumatic-driven glove. The controller deadzone variable was also introduced to the SMC controller design for noise rejection. The value of the introduce variable contains a static term and a proportional term to the reference pressure. When applying the SMC, the system is more robust against the modeling uncertainties of the soft actuators. However, the high control gain of the SMC also over stiff those actuators.The challenges for low-level controller design are related to the actuation mechanism. For pneumatic-driven systems, the pneumatic dynamics is important since it shows slower and more nonlinear response compared with electromagnetic system [34]. For cable-driven system, compensation algorithms are preferred when friction, hysteresis and tendon coupling are severe [128].

Experiment and Evaluation with Human

Wearable soft robots have been tested on both healthy users and impaired users with slightly different goals. During healthy participant testing, the primary goals are to justify the design requirements, evaluate the overall benefit for healthy users, and provide preliminary evidence for the potential benefit on impaired users. Metabolic cost [26, 106••, 129] and muscle effort [105, 121, 122, 126, 130] are the two primary evaluation criteria for healthy users. For impaired user studies, the goal is concentrated on evaluating the users potential benefit when wearing the device and improvements in functional evaluation tasks are another main criterion for impaired users [107••, 109, 111, 115, 131, 132].

The metabolic cost reflects the overall energy changes when a wearable robot actively assists a user. In [26], a preliminary study was conducted on four healthy users to determine the gross benefit (device active versus device worn but inactive). A statistically significant reduction of the averaged metabolic was observed with the device being active. In [106••], a study was conducted on three healthy users to evaluate the benefit of an untethered soft hip exosuit. The metabolic cost was reduced by 15.28% when full gait cycle assisted was compared with no device condition. Compared to the case without a soft robot, a minimal increase in the metabolic cost is expected with a passive soft wearable robot, and a reduction in metabolic cost is expected when the device is active. The metabolic cost can provide an overview of the benefits of a soft wearable robot, but it cannot provide details on the kinematic and kinetic changes of the assisted joint(s).

The muscle effort, in contrast to the metabolic cost, indicates the changes of a specific muscle or muscle group's activity when the attached device is active versus inactive [133]. sEMG sensors are the commonly used non-invasive tools to estimate muscle force. In [105], a soft inflatable knee exosuit was tested on one healthy participant to assist the knee extension during the swing phase. Five sEMG sensors were attached to the lower limb to evaluate the muscle efforts (device active versus inactive). A reduction was observed for the quadriceps when the device was active. Similarly, in [119], a polyvinyl chloride gel soft hip actuator was tested on one stroke patient with sEMG sensors attached to the lower limb. It was demonstrated that the device could reduce the burden on the lower limbs' muscles during walking with an approximate reduction of 17% for the rectus femoris muscle, 11% for the Sartorius, and 5% for the hamstring. Similar to the metabolic cost, wearing a passive soft wearable robot may not significantly increase the muscle effort and a reduction is also expected when the robot is active. Although sEMG sensors provide reliable muscle force estimation, its performance is quite sensitive to factors like skin conditions, external load on the sensing area.

The improvements in functional evaluation task reflects the impaired user's performance changes in a specific functional task when a soft wearable robot is turned on. In [107••], a soft supernumerary finger was attached to one impaired user to regain the grasping function. The Box and Block Test and the Franchy Arm Test were performed on the participant, and improvements were observed in both cases. In [27], a soft knee exosuit was applied to three impaired participants. A timed up-and-go test was performed to evaluate the device performance during overground waking and a reduction on execution time was observed. In [134], a cable-driven soft exosuit was tested on six participants in chronic phase after the stroke. Both 10-meter walk and six minute walk tests were conducted for all impaired users. Compared to the inactive case, the user walked 0.14 m/s during the first test and traveled 32 m farther during the second test on average. Similarly in [135], the cable-driven soft exosuits were mounted on 44 post-stroke user for treadmill and over ground training. After a 5 days training session with the device active, the averaged maximum walking speed for both device-assisted and unassisted were increased by 0.1 m/s and 0.07 m/s. The functional evaluation task is specifically selected for each class of the impaired user and the assistance from the soft robots.

It should be noted that while both soft and rigid wearable robots have been tested on healthy or impaired users, limited research directly compares the performance of rigid and soft robots [136], which presents an exciting topic for future research. In general, soft wearable robots have a great potential for assisting activities of daily living without close supervision by medical professionals because of their advantages in safety [137] and comfort [138]. Due to the use of soft materials, human users will be at a lower risk even when the actuators malfunction or misalign with the human joints, compared to their rigid counterparts. While both active rigid and soft robots have been shown to be effective for healthy and impaired users, only soft robots can be worn passively without significantly increasing metabolic costs [106••] or muscle efforts [119]. Hence, a user can wear these soft robots for a long time without feeling uncomfortable. Despite many advantages, there are still inherent problems yet to be resolved in soft wearable robots, such as friction in cable-driven systems [110••] and slow response in the fluid-driven systems [105].

Discussions of Open Challenges

Remaining Challenges

While some exciting progress has been made in different aspects of wearable soft robots, we identify several challenges that need to be addressed by the research community. We hope a summary of these challenges will inspire more interdisciplinary efforts to improve the safety, reliability, and intelligence of wearable soft robots.

Novel Designs to Support Sophisticated and Fast Human Motions One major challenge in wearable soft robots is that most current designs only assist a single degree-of-freedom motion. There are very few robots that can assist a full spherical joint motion or full hand functions which include joints with different ranges and directions compacted in limited space. To achieve complex motion profiles, actuators with multiple degree of freedom is needed [139]. Another challenge in wearable soft robots is their slow responses. For fluidic actuators, the inflation and deflation process takes time. To solve that, the most simple way is to increase flow rate. With limited flow rate, energy can be restored and release when fast actuation is needed, and some potential mechanisms include spring systems and bistable structures [140, 141]. In some cases, there is an challenge to maintain the compliance and comfortability of soft robots when rigid components are necessary. There is not an clear boundary between rigid and soft wearable robots. It is important to determine appropriate stiffness of wearable soft robots to assure both device functionality and its safety and compatibility with human.

Novel Fusion Algorithms for Soft Sensors A common challenge in wearable soft sensors includes characterizing non-linearity and hysteresis due to the viscoelasticity of the materials. Several works have implemented machine learning algorithms to learn the complex dynamics of soft sensors in wearable applications. To achieve this, extensive data sets are required for training the model, which are often highly dependant on the specific experimental and sensor conditions. In soft sensor wearable applications, it is common to observe shifting of the sensor location over the body, as the interfaces are usually compliant and allow relative motion. This introduces unreliability, hysteresis and drift of the sensor measurements. As such, there is a need for stand-alone models that take into account shifting of the sensors and introduces compensation methods to maintain performance. Introducing sensor shift-adaptive models complementary to the characterization model could help improve sensor reliability and robustness for dynamic and long-term applications.

Autonomous Operation for Personalized Assistance The main challenge for the controller design for wearable soft robotics is to find a personalized assistance profile for each individual. This challenge requires either a more accurate description of the human dynamics or a more robust controller to cover the uncertainties from the simplified model. However, introducing more sophisticated analytical model can lead to a significant increase of the computational cost [34, 142]. Efficient data collection is still missing for model-free methods. The tasks during the training sessions need to be investigated so that the algorithm can capture the dynamics of the human [143]. One possible solution for modeling uncertainties is robust control approaches but such methods could increase the control gain, which makes the soft actuator more sensitive to tracking errors and less compliant [144].

Conclusions

Wearable soft robotics is a fast emerging field that has seen significant advances in actuator, sensor and controller designs. The safety, compliance and light weight of wearable soft robots make them a promising candidate to assist humans in various tasks and augment their capabilities. This article reviews the recent trend in the field of wearable soft robots with a focus in actuator, sensor, and controller designs.

Fluid and cable-driven actuators and shape-memory alloy actuators are popular types of actuators applicable to wearable soft devices. There are remaining challenges in design of wearable soft robots to support multiple degree-of-freedom motion, improve actuation speeds in fluidic actuators, and usage of rigid components.

The compliant characteristic of wearable soft sensors allows sensing different types of physical deformations that extend over the capabilities of traditional rigid sensors. A recent trend in the design of soft multimodal and multi-functional sensors has allowed improved form factor and a more robust recognition of multiple deformation modes.

Multi-level controller becomes the most commonly use method for wearable soft device. The high-level controller maps the sensor measurements to the desired trajectory for the actuator while the low-level controller closed the loop internally to track the trajectory. Both model-based and model free methods have been explored in the design of the high-level and low-level controllers. A combination of model-based and model-free method could be a viable direction towards making future wearable soft robots adaptive to different users and various tasks.

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Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent All reported studies/experiments with human or animal subjects performed by the authors have been previously published and complied with all applicable ethical standards (including the Helsinki declaration and its amendments, institutional/national research committee standards, and international/national/institutional guidelines).

References

Papers of particular interest, published recently, have been highlighted as:
- • Of importance
- •• Of major importance

1. Nguyen PH, Zhang W. Design and computational modeling of fabric soft pneumatic actuators for wearable assistive devices. Sci Rep. 2020 :1–13.
2. Nguyen PH, Imran Mohd IB, Sparks C, Arellano FL, Zhang W, Polygerinos P. Fabric soft poly-limbs for physical assistance of daily living tasks. In: Proceedings of IEEE ICRA; 2019a. p. 8429–8435.
3. Sridar S, Poddar S, Tong Y, Polygerinos P, Zhang W. Towards untethered soft pneumatic exosuits using low-volume inflatable actuator composites and a portable pneumatic source. IEEE RA-L. 2020a;5(3):4062–4069.
4. Zhou YM, Hohimer C, Proietti T, O'Neill CT, Walsh C. Kinematics-based control of an inflatable soft wearable robot for assisting the shoulder of industrial workers. IEEE RA-L. 2021;6(2):2155–2162.
5. Frisoli A. Wearable Robots. Berlin: Springer; 2019, pp. 1–8.
6. Pons JL. Wearable robots: biomechatronic exoskeletons. Hoboken: Wiley; 2008.
7. Channa A, Popescu N, Ciobanu V. Wearable solutions for patients with parkinson's disease and neurocognitive disorder: A systematic review. Sensors. 2020;20(9):2713.
8. Theurel J, Desbrosses K. Occupational exoskeletons: Overview of their benefits and limitations in preventing work-related musculoskeletal disorders. IISE Trans Occup Ergon Hum Factors. 2019;7(3-4):264–280.
9. Elevate Ski, Roam Robotics, a. URL https://www.roamrobotics.com/elevate.
10. Chen B, Ma H, Qin L-Y, Gao F, Chan K-M, Law S-W, Qin L, Liao W-H. Recent developments and challenges of lower extremity exoskeletons. J Orthop Translat. 2016;5:26–37.
11. Cirstea CM. Are wearable robots effective for gait recovery after stroke? Stroke. 2019;50(12):3337–3338.
12. Kubota S, Nakata Y, Eguchi K, Kawamoto H, Kamibayashi K, Sakane M, Sankai Y, Ochiai N. Feasibility of rehabilitation training with a newly developed wearable robot for patients with limited mobility. Arch Phys Med Rehabil. 2013;94(6):1080–1087.
13. Zanotto D, Akiyama Y, Stegall P, Agrawal SK. Knee joint misalignment in exoskeletons for the lower extremities:

effects on user's gait. IEEE Trans Robot. 2015;31(4):978–987.
14. Banerjee H, Tse ZTH, Ren H. Soft robotics with compliance and adaptation for biomedical applications and forthcoming challenges. Int J Robot Autom. 2018;33(1):69–80.
15. Thalman C, Artemiadis P. A review of soft wearable robots that provide active assistance Trends, common actuation methods, fabrication, and applications. Wearable Technol. 2020;1:e3.
16. Lee C, Kim M, Kim YJ, Hong N, Ryu S, Kim HJ, Kim S. Soft robot review. Int J Control Autom Syst. 2017;15(1):3–15.
17. Saggio G, Riillo F, Sbernini L, Quitadamo LR. Resistive flex sensors: a survey. Smart Mater Struct. 2016;25(1):013001.
18. Chossat J-B, Park Y-L, Wood R, Duchaine V. A soft strain sensor based on ionic and metal liquids. IEEE Sens J. 2013;13(9):3405–3414.
19. Leal-Junior AG, Frizera A, Vargas-Valencia L, dos Santos WM, Bo APL, Siqueira AAG, Pontes MJ. Polymer optical fiber sensors in wearable devices toward novel instrumentation approaches for gait assistance devices. IEEE Sens J. 2018a;9(17):7085–7092.
20. Agarwal G, Besuchet N, Audergon B, Paik J. Stretchable materials for robust soft actuators towards assistive wearable devices. Sci Rep. 2016;6(1):34224.
21. Asbeck AT, De Rossi SMM, Galiana I, Ding Y, Walsh C. Stronger, smarter, softer: next-generation wearable robots. IEEE Robot Autom Mag. 2014;21(4):22–33.
22. Kanjanapas S, Nunez CM, Williams SR, Okamura AM, Luo M. Design and analysis of pneumatic 2-DoF soft haptic devices for shear display. IEEE RA-L. 2019;4(2):1365–1371.
23. El-Atab N, Mishra RB, Al-Modaf F, Joharji L, Alsharif AA, Alamoudi H, Diaz M, Qaiser N, Hussain MM. Soft actuators for soft robotic applications: a review. Adv Intell Syst. 2020;2(10):2000128.
24. Heikenfeld J, Jajack A, Rogers J, Gutruf P, Tian L, Pan T, Li R, Khine M, Kim J, Wang J, Kim J. Wearable sensors: modalities, challenges, and prospects. Lab on a Chip. 2018;18(2):217–248.
25. Park M, Jeong B, Park Y-L. Hybrid system analysis and control of a soft robotic gripper with embedded proprioceptive sensing for enhanced gripping performance. Adv Intell Syst. 2021 :2000061.
26. Asbeck AT, Rossi SMMD, Holt KG, Walsh C. A biologically inspired soft exosuit for walking assistance. IJRR. 2015;34(6):744–762.
27. Sridar S, Qiao Z, Rascon A, Biemond A, Beltran A, Maruyama T, Kwasnica C, Polygerinos P, Zhang W. Evaluating immediate benefits of assisting knee extension with a soft inflatable exosuit. IEEE Trans Med Robot Bionics. 2020b;2(2):216–225.
28. HeroWear. https://herowearexo.com/.
29. Roam Robotics, b. https://www.roamrobotics.com/.
30. ReStore, ReWalk Robotics. https://rewalk.com/restore-exo-suit/.
31. Sanchez V, Walsh C, Wood R. Textile technology for soft robotic and autonomous garments. Adv Funct Mater. 2020 :2008278.
32. Liu Q, Zuo J, Zhu C, Xie SQ. Design and control of soft rehabilitation robots actuated by pneumatic muscles: state of the art. Future Gener Comput Syst. 2020a;113:620–634.
33. Kim D, Kim S-H, Kim T, Kang BB, Lee M, Park W, Ku S, Kim DW, Kwon J, Lee H, Bae J, Park Y-L, Cho K-J, Jo S. Review of machine learning methods in soft robotics. PLOS ONE. 2021;16(2):e0246102.
34. Thuruthel TG, Ansari Y, Falotico E, Laschi C. Control strategies for soft robotic manipulators a survey. Soft Robot. 2018;5(2):149–163.
35. Xiloyannis M, Chiaradia D, Frisoli A, Masia L. Physiological and kinematic effects of a soft exosuit on arm movements. J Neuroeng Rehabil. 2019;16(1):1–15.
36. Bae J, Siviy C, Rouleau M, Menard N, Odonnell K, Geliana I, Athanassiu M, Ryan D, Bibeau C, Sloot L, Kudzia P, Ellis T, Awad L, Walsh C. A lightweight and efficient portable soft exosuit for paretic ankle assistance in walking after stroke. In: Proceedings of IEEE ICRA; 2018. p. 2820–2827.
37. In H, Kang BB, Sin MK, Cho KJ. Exo-Glove: A wearable robot for the hand with a soft tendon routing system. IEEE Robot Autom Mag. 2015;22(1):97–105.
38. Hussain I, Salvietti G, Spagnoletti G, Prattichizzo D. The soft-sixthfinger: a wearable EMG controlled robotic extra-finger for grasp compensation in chronic stroke patients. IEEE RA-L. 2016a;1(2):1000–1006.
39. O'Neill CT, Phipps NS, Cappello L, Paganoni S, Walsh C. A soft wearable robot for the shoulder Design, characterization, and preliminary testing. In: Proceedings of IEEE ICORR; 2017. p. 1672–1678.
40. Koh TH, Cheng N, Yap HK, Yeow CH. Design of a soft robotic elbow sleeve with passive and intent-controlled actuation. Front Neurosci. 2017;11(OCT):1–12.
41. Park YL, Chen B, Pérez-Arancibia NO, Young D, Stirling L, Wood R, Goldfield EC, Nagpal R. Design and control of a bio-inspired soft wearable robotic device for ankle-foot rehabilitation. Bioinspir Biomim. 2014 ;9(1).
42. Polygerinos P, Wang Z, Galloway KC, Wood R, Walsh C. Soft robotic glove for combined assistance and at-home rehabilitation. Rob Auton Syst. 2015a;73:135–143.
43. Heung KHL, Tong RKY, Lau ATH, Li Z. Robotic glove with soft-elastic composite actuators for assisting activities of daily living. Soft Robot. 2019;6(2):289–304.
44. Robertson MA, Kara OC, Paik J. Soft pneumatic actuator-driven origami-inspired modular robotic "pneumagami" IJRR. 2020.
45. Nguyen PH, Sparks C, Nuthi SG, Vale NM, Polygerinos P. Poly-Limbs: Soft toward a new paradigm of mobile manipulation for daily living tasks. Soft Robotics. 2019b;6(1):38–53.
46. Skorina EH, Luo M, Onal CD. A soft robotic wearable wrist device for kinesthetic haptic feedback. Front Robot AI. 2018;5(JUN):1–11.
47. Ge L, Chen F, Wang D, Zhang Y, Han D, Wang T, Gu G. Design, modeling, and evaluation of fabric-based pneumatic actuators for soft wearable assistive gloves. Soft Robot. 2020;7(5):583–596.
48. Sridar S, Nguyen PH, Zhu M, Lam QP, Polygerinos P. Development of a soft-inflatable exosuit for knee rehabilitation. In: Proceedings of IEEE IROS; 2017. p. 3722–3727.
49. Liang X, Cheong H, Chui CK, Yeow CH. A fabric-based wearable soft robotic limb. J Mech Robot. 2019;11(3):1–7.
50. Jeong J, Yasir IB, Han J, Park CH, Bok S-K, Kyung K-U. Design of shape memory alloy-based soft wearable robot for assisting wrist motion. Appl Sci. 2019;9(19):4025.
51. Park S, Park CH. Suit-type wearable robot powered by shape-memory-alloy-based fabric muscle. Sci Rep. 2019;9(1):1–8.
52. Copaci D, Cano E, Moreno L, Blanco D. New design of a soft robotics wearable elbow exoskeleton based on shape memory alloy wire actuators. Appl Bionics Biomech. 2017.
53. Kang BB, Choi H, Lee H, Cho KJ. Exo-Glove Poly II: A polymer-based soft wearable robot for the hand with a tendon-driven actuation system. Soft Robotics. 2019;6(2):214–227.

54. Baik S, Park S, Park J. Haptic Glove Using Tendon-Driven Soft Robotic Mechanism. Front Bioeng Biotechnol. 2020;8(OCT):1–12.
55. Varghese RJ, Lo BPL, Yang G-Z. Design and prototyping of a bio-inspired kinematic sensing suit for the shoulder joint: Precursor to a multi-dof shoulder exosuit. IEEE RA-L. 2020;5(2):540–547.
56. Ye D, Kim M, Kuindersma S, Walsh C. Human-in-the-loop optimization of hip assistance with a soft exosuit during walking. Sci Robot. 2018;3(15):1–9.
57. Chen D, Yun Y, Deshpande AD. Experimental characterization of Bowden cable friction. In: Proceedings of IEEE ICRA; 2014. p. 5927–5933.
58. Hadi A, Alipour K, Kazeminasab S, Elahinia M. ASR glove: A wearable glove for hand assistance and rehabilitation using shape memory alloys. J Intell Mater Syst Struct. 2018;29(8):1575–1585.
59. Chernyshov G, Tag B, Caremel C, Cao F, Liu G, Kunze K. Shape memory alloy wire actuators for soft, wearable haptic devices. In: Proceedings of ACM ISWC; 2018. p. 112–119.
60. Jani JM, Leary M, Subic A, Gibson MA. A review of shape memory alloy research, applications and opportunities. Mater Des. 2014;56:1078–1113.
61.•• Kim D, Kwon J, Han S, Park Y-L, Jo S. Deep full-body motion network for a soft wearable motion sensing suit. IEEE ASME Trans Mechatron. 2019;24(1):56–66. **Full body motion tracking was achieved through a proposed deep learning method that utilizes information from 20 soft strain sensors distributed over the users body.**
62.• Kim K, Shin S, Kong K. An air-filled pad with elastomeric pillar array designed for a force-sensing insole. IEEE Sens J. 2018;18(10):3968–3976. **A soft force-sensing pad with elastomeric pillar array based on pneumatic pressure sensing was designed to measure foot ground contact forces.**
63. Holleczek T, Ru A, Harms H, Tro G. Textile pressure sensors for sports applications. In: 2010 IEEE Sensors. IEEE; 2010. p. 732–737.
64. To C, Hellebrekers T, Jung J, Yoon SJ, Park Y-L. A Soft Optical Waveguide Coupled With Fiber Optics for Dynamic Pressure and Strain Sensing. IEEE RA-L. 2018;3(4):3821–3827.
65. Park Y-L, Chen B-R, Wood R. Design and fabrication of soft artificial skin using embedded microchannels and liquid conductors. IEEE Sens J. 2012;12(8):2711–2718.
66.•• Kim T, Lee S, Hong T, Shin G, Kim T, Park Y-L. Heterogeneous sensing in a multifunctional soft sensor for human-robot interfaces. Sci Robot. 2020;5(49):eabc6878. **A novel multifunctional soft sensor was designed capable of sensing multiple modalities and decoupling combined deformation modes through machine learning techniques.**
67. Ye Q, Ye T, Sun S, Hu J, Wang Y, Zhang Z, Liu A, Cheng H, Gao W, Zhang W, Chai H, Wu H. Bioinspired, multifunctional dual-mode pressure sensors as electronic skin for decoding complex loading processes and human motions. Nano Energy. 2020;78(12):105337.
68. Liu S, Shah DS, Kramer-Bottiglio R. Highly stretchable multilayer electronic circuits using biphasic galliumindium. Nat Mater. 2021.
69. Chossat J-B, Tao Y, Duchaine V, Park Yong-Lae. Wearable soft artificial skin for hand motion detection with embedded microfluidic strain sensing. In: Proceedings of IEEE ICRA. IEEE; 2015. p. 2568–2573.
70. Frutiger A, Muth JT, Vogt DM, Mengüç Y, Campo A, Valentine AD, Walsh C, Lewis JA. Capacitive soft strain sensors via multicore-shell fiber printing. Adv Mater. 2015;27(15):2440–2446.
71. Atalay O, Atalay A, Gafford J, Wang H, Wood R, Walsh C. A highly stretchable capacitive-based strain sensor based on metal deposition and laser rastering. Adv Mater Technol. 2017a;2(9):1700081.
72. Harnett CK, Zhao H, Shepherd RF. Stretchable optical fibers: threads for strain-sensitive textiles. Adv Mater Technol. 2017;2(9):1700087.
73. Souri H, Banerjee H, Jusufi A, Radacsi N, Stokes AA, Park I, Sitti M, Amjadi M. Wearable and stretchable strain sensors: materials, sensing mechanisms, and applications. Adv Intell Syst. 2020;2(8):2000039.
74. Kim DongWook, Kwon J, Jeon B, Park Y-L. Adaptive calibration of soft sensors using optimal transportation transfer learning for mass production and long-term usage. Adv Intell Syst. 2020b;2(6):1900178.
75. Lu S, Chen D, Liu C, Jiang Y, Wang M. A 3-d finger motion measurement system via soft strain sensors for hand rehabilitation. Sens Actuator A Phys. 2019;285:700–711.
76. Russo S, Ranzani T, Liu H, Nefti-Meziani S, Althoefer K, Menciassi A. Soft and stretchable sensor using biocompatible electrodes and liquid for medical applications. Soft Robotics. 2015;2(4):146–154.
77. Atalay A, Sanchez V, Atalay O, Vogt DM, Haufe F, Wood R, Walsh C. Batch fabrication of customizable silicone-textile composite capacitive strain sensors for human motion tracking. Adv Mater Technol. 2017;2(9):1700136.
78. Park Y-L, Majidi C, Kramer R, Bérard P, Wood R. Hyperelastic pressure sensing with a liquid-embedded elastomer. J Micromech Microeng. 2010;20(12):125029.
79. Vogt DM, Park Y-L, Wood R. Design and characterization of a soft multi-axis force sensor using embedded microfluidic channels. IEEE Sens J. 2013;13(10):4056–4064.
80. Atalay O, Atalay A, Gafford J, Walsh C. A highly sensitive capacitive-based soft pressure sensor based on a conductive fabric and a microporous dielectric layer. Adv Mater Technol. 2018;3(1):1700237.
81. Araromi OA, Walsh C, Wood R. Hybrid carbon fiber-textile compliant force sensors for high-load sensing in soft exosuits. In: Proceedings of IEEE IROS. IEEE; 2017. p. 1798–1803.
82. Araromi OA, Castellanos S, Walsh C, Wood R. Compliant low profile multi-axis force sensors. In: Proceedings of IEEE ICRA. IEEE; 2018. p. 187–192.
83. Choi H, Kong K. A soft three-axis force sensor based on radially symmetric pneumatic chambers. IEEE Sens J. 2019;19(13):5229–5238.
84. Kong K, Tomizuka M. A gait monitoring system based on air pressure sensors embedded in a shoe. IEEE ASME Trans Mechatron. 2009;14(3):358–370.
85. Majidi C, Kramer R, Wood R. A non-differential elastomer curvature sensor for softer-than-skin electronics. Smart Mater Struct. 2011;20(10):105017.
86. Kramer RK, Majidi C, Sahai R, Wood R. Soft curvature sensors for joint angle proprioception. In: Proceedings of IEEE IROS. IEEE; 2011. p. 1919–1926.
87. Mishra V, Kiourti A. Wrap-around wearable coils for seamless monitoring of joint flexion. IEEE Trans Biomed Eng. 2019;10(10):2753–2760.
88. Sun X, Felton SM, Wood RJ, Kim S. Printing angle sensors for foldable robots. In: Proceedings of IEEE IROS. IEEE; 2015. p. 1725–1731.

89. Sabri N, Aljunid SA, Salim MS, Fouad S. Fiber optic sensors: short review and applications. In: Springer series in materials science. Springer; 2015. p. 299–311.
90. Van Meerbeek IM, De Sa CM, Shepherd RF. Soft optoelectronic sensory foams with proprioception. Sci Robot. 2018;3(24):eaau2489.
91. Ponraj G, Ren H. Sensor fusion of leap motion controller and flex sensors using kalman filter for human finger tracking. IEEE Sens J. 2018;18(5):2042–2049.
92. Tognetti A, Lorussi F, Carbonaro N, de Rossi D. Wearable goniometer and accelerometer sensory fusion for knee joint angle measurement in daily life. Sensors. 2015;15(11):28435–28455.
93. Leal-Junior AG, Vargas-Valencia L, dos Santos WM, Schneider FBA, Siqueira AAG, Pontes MJ, Frizera A. POF-IMU sensor system: A fusion between inertial measurement units and POF sensors for low-cost and highly reliable systems. Opt Fiber Technol. 2018b;43:82–89.
94.• Vargas-Valencia L, Schneider FBA, Leal-Junior AG, Caicedo-Rodriguez P, Sierra-Arevalo WA, Rodriguez-Cheu LE, Bastos-Filho T, Frizera-Neto A. Sleeve for knee angle monitoring: an IMU-POF sensor fusion system. IEEE J Biomed Health Inform. 2021;25(2):465–474. **A wearable soft polymer optical fiber (POF) sensor was designed to measure knee joint kinematics, and complemented with a Multiplicative Extended Kalman Filter (MEKF) fusion algorithm that combines IMU sensor information to improve accuracy and repeatability.**
95. Jin Y, Glover CM, Cho H, Araromi OA, Graule MA, Na L, Wood R, Walsh C. Soft sensing shirt for shoulder kinematics estimation. In: Proceedings of IEEE ICRA. IEEE; 2020. p. 4863–4869.
96. Tavassolian M, Cuthbert TJ, Napier C, Peng JY, Menon C. Textile-based inductive soft strain sensors for fast frequency movement and their application in wearable devices measuring multiaxial hip joint angles during running. Adv Intell Syst. 2020;2(4):1900165.
97. Yang J, Yin Y. Novel soft smart shoes for motion intent learning of lower limbs using LSTM with a convolutional autoencoder. IEEE Sens J. 2021;1(2):1906–1917.
98. Chen Z, Wu R, Guo S, Liu X, Fu H, Jin X, Liao M. 3D upper body reconstruction with sparse soft sensors. Soft Robotics. 2020a. page soro.2019.0187.
99. Greff K, Srivastava RK, Koutnik J, Steunebrink BR, Schmidhuber J. LSTM: a search space odyssey. IEEE Trans Neural Networks Learn Syst. 2017;28(10):2222–2232.
100. Kim D, Kim M, Kwon J, Park Yong-Lae, Jo S. Semi-supervised gait generation with two microfluidic soft sensors. IEEE RA-L. 2019b;4(3):2501–2507.
101. Prado A, Cao X, Ding X, Agrawal SK. Prediction of gait cycle percentage using instrumented shoes with artificial neural networks. In: Proceedings of IEEE ICRA; 2020. p. 2834–2840. Institute of Electrical and Electronics Engineers Inc.
102. González I, Fontecha J, Hervás R, Bravo J. An ambulatory system for gait monitoring based on wireless sensorized insoles. Sensors. 2015;15(7):16589–16613.
103. Mohammed S, Samé A, Oukhellou L, Kong K, Huo W, Amirat Y. Recognition of gait cycle phases using wearable sensors. Rob Auton Syst. 2016;75:50–59.
104.• Polygerinos P, Galloway KC, Sanan S, Herman M, Walsh C. Emg controlled soft robotic glove for assistance during activities of daily living. In: Proceedings of IEEE ICORR; 2015b. p. 55–60. **A three-state (grasp, release, and hold) FSM system for a soft glove was designed and the system provided constant direct assistance in each state**.
105. Sridar S, Qiao Z, Muthukrishnan N, Zhang W, Polygerinos P. A soft-inflatable exosuit for knee rehabilitation Assisting swing phase during walking. Front Robot AI. 2018;5:44.
106.•• Cao W, Chen C, Hu H, Fang K, Wu X. Effect of hip assistance modes on metabolic cost of walking with a soft exoskeleton. IEEE Trans Autom Sci Eng. 2020. **Two states: hip extension and hip flexion were identified through the measurements of local sensors. In each state, the assistive torque profile was either calculated from the biological hip torque model or set to zero to investigate the performance of different combinations.**
107.•• Hussain I, Meli L, Pacchierotti C, Prattichizzo D. A soft robotic supernumerary finger and a wearable cutaneous finger interface to compensate the missing grasping capabilities in chronic stroke patients. In: Proceedings of World Haptics Conference; 2017. p. 183–188. **A soft supernumerary finger was attached to one impaired user for regaining the grasping function. The Box and Block Test and the Franchy Arm Test were performed on the participant, and improvements were observed in both cases**.
108. Liu S, Zhu Y, Zhang Z, Fang Z, Tan J, Peng J, Song C, Asada H, Wang Z. Otariidae-inspired soft-robotic supernumerary flippers by fabric kirigami and origami. IEEE ASME Trans Mechatron. 2020b.
109. Tang ZQ, Ho LH, Tong KY, Li Z. Model-based online learning and adaptive control for a “human-wearable soft robot” integrated system. IJRR page 0278364919873379. 2019.
110.•• Yang X, Huang T-H, Hu H, Yu S, Zhang S, Zhou X, Carriero A, Yue G, Su H. Spine-inspired continuum soft exoskeleton for stoop lifting assistance. IEEE RA-L. 2019;4(4):4547–4554. **The controller was designed to assist stoop lifting utilizing the simplified bending model of the lumbar spine. The bending model described the relationship between the assistive force and the forces in the human spines. Then the assistive force was converted into desired angular position, velocity and acceleration for the actuator**.
111. Ciullo AS, Veerbeek JM, Temperli E, Luft AR, Tonis FJ, Haarman CJW, Ajoudani A, Catalano M, Held JPO, Bicchi A. A novel soft robotic supernumerary hand for severely affected stroke patients. IEEE Trans Neural Syst Rehabil Eng. 2020;28(5):1168–1177.
112. Ha J, Kim D, Jo S. Use of deep learning for position estimation and control of soft glove. In: Proceedings of IEEE ICCAS; 2018. p. 570–574.
113. Kim D, Kang BB, Kim KB, Choi H, Ha J, Cho K-J, Jo S. Eyes are faster than hands: A soft wearable robot learns user intention from the egocentric view. Sci Robot. 2019c;4(26):eaav2949.
114.• Schlagenhauf C, Bauer D, Chang K-H, King JP, Moro D, Coros S, Pollard N. Control of tendon-driven soft foam robot hands. In: Proceedings of IEEE-RAS Humanoids; 2018. p. 1–7. **A performance comparison among supervised learning, reinforcement learning, k nearest neighbor (kNN) and linear ridge regression methods were discussed with a cable-driven soft hand. The result indicated that kNN method outperformed other techniques in the simulation**.
115. Zhou Y, Wagner D, Nuckols K, Heimgartner R, Correia C, Clarke M, Orzel D, O’Neill C, Solinsky R, Paganoni S, et al. Soft robotic glove with integrated sensing for intuitive grasping assistance post spinal cord injury. In: Proceedings of IEEE ICRA; 2019. p. 9059–9065.

116. Hunte K, Chen S, Yi J, Su H. Assist-as-needed control of a wearable lightweight knee robotic device. In: Proceedings of IEEE/ASME AIM; 2020. p. 1477–1482.
117. Polygerinos P, Wang Z, Galloway KC, Wood R, Walsh C. Soft robotic glove for combined assistance and at-home rehabilitation. Rob Auton Syst. 2015c;73:135–143.
118. Skorina EH, Tao W, Chen F, Luo M, Onal CD. Motion control of a soft-actuated modular manipulator. In: Proceedings of IEEE ICRA; 2016. p. 4997–5002.
119. Li Y, Hashimoto M. Pvc gel soft actuator-based wearable assist wear for hip joint support during walking. Smart Mater Struct. 2017;26(12):125003.
120. Guggenheim J, Hoffman R, Song H, Asada HH. Leveraging the human operator in the design and control of supernumerary robotic limbs. IEEE RA-L. 2020;5(2):2177–2184.
121. Kim W, Balatti P, Lamon E, Ajoudani A. Moca-man: A mobile and reconfigurable collaborative robot assistant for conjoined human-robot actions. In: Proceedings of IEEE ICRA; 2020c. p. 10191–10197.
122. Al-Fahaam H, Davis S, Nefti-Meziani S, Theodoridis T. Novel soft bending actuator-based power augmentation hand exoskeleton controlled by human intention. Intell Serv Robot. 2018;11(3):247–268.
123. Wang Q, Zhou Z, Zhang Z, Lou Y, Zhou Y, Zhang S, Chen W, Mao C, Wang Z, Lou W, et al. An underwater lower-extremity soft exoskeleton for breaststroke assistance. IEEE Trans Med Robot Bionics. 2020;2(3):447–462.
124. Lv G, Zhu H, Gregg RD. On the design and control of highly backdrivable lower-limb exoskeletons: A discussion of past and ongoing work. IEEE Control Syst Mag. 2018;38(6):88–113.
125. Roerdink M, Lamoth CJC, Beek PJ, et al. Online gait event detection using a large force platform embedded in a treadmill. J Biomech. 2008;41(12):2628–2632.
126. Masia L, Hussain I, Xiloyannis M, Pacchierotti C, Cappello L, Malvezzi M, Spagnoletti G, Antuvan C, Khanh D, Pozzi M, Prattichizzo D. Soft wearable assistive robotics: exosuits and supernumerary limbs. In: Wearable Exoskeleton Systems: Design, control and applications; 2018. p. 219–254. Institution of Engineering and Technology.
127. Lotti N, Xiloyannis M, Durandau G, Galofaro E, Sanguineti V, Masia L, Sartori M. Adaptive model-based myoelectric control for a soft wearable arm exosuit: A new generation of wearable robot control. IEEE Robot Autom Mag. 2020;27(1):43–53.
128. Xu K, Simaan N. Actuation compensation for flexible surgical snake-like robots with redundant remote actuation. In: Proceedings of IEEE ICRA; 2006. p. 4148–4154.
129. Ye D, Galiana I, Siviy C, Panizzolo FA, Walsh C. Imu-based iterative control for hip extension assistance with a soft exosuit. In: Proceedings of IEEE ICRA; 2016. p. 3501–3508.
130. Yu Shuangyue, Huang T-H, Wang D, Lynn B, Sayd D, Silivanov V, Park YS, Tian Y, Hao Su. Design and control of a high-torque and highly backdrivable hybrid soft exoskeleton for knee injury prevention during squatting. IEEE RA-L. 2019;4(4):4579–4586.
131. Siviy C, Bae J, Baker L, Porciuncula F, Baker T, Ellis TD, Awad LN, Walsh C. Offline assistance optimization of a soft exosuit for augmenting ankle power of stroke survivors during walking. IEEE RA-L. 2020;5(2):828–835.
132. Hussain I, Spagnoletti G, Salvietti G, Prattichizzo D. An emg interface for the control of motion and compliance of a supernumerary robotic finger. Front Neurorobot. 2016b;10:18.
133. Theurel J, Desbrosses K, Roux T, Savescu A. Physiological consequences of using an upper limb exoskeleton during manual handling tasks. Appl Ergon. 2018;67:211–217.
134. Awad LN, Kudzia P, Revi DA, Ellis TD, Walsh C. Walking faster and farther with a soft robotic exosuit: implications for post-stroke gait assistance and rehabilitation. IEEE Open J Eng Med Biol. 2020a;1:108–115.
135. Awad LN, Esquenazi A, Francisco GE, Nolan KJ, Jayaraman A. The rewalk restore® soft robotic exosuit: a multi-site clinical trial of the safety, reliability, and feasibility of exosuit-augmented post-stroke gait rehabilitation. J Neuroeng Rehabil. 2020b;17(1):1–11.
136. Chiaradia D, Xiloyannis M, Solazzi M, Masia L, Frisoli A. Comparison of a soft exosuit and a rigid exoskeleton in an assistive task. In: WeRob. Springer; 2018. p. 415–419.
137. Pang G, Yang G, Heng W, Ye Z, Huang X, Yang H-Y, Pang Z. Coboskin: Soft robot skin with variable stiffness for safer human–robot collaboration. IEEE Trans Ind Electron. 2020;68(4):3303–3314.
138. Koizumi S, Chang T-H, Nabae H, Endo G, Suzumori K, Mita M, Saitoh K, Hatakeyama K, Chida S, Shimada Y. Soft robotic gloves with thin mckibben muscles for hand assist and rehabilitation. In: Proceedings of IEEE/SICE SII; 2020. p. 93–98.
139. Choi WH, Kim S, Lee D, Shin D. Soft, Multi-DoF, variable stiffness mechanism using layer jamming for wearable robots. IEEE RA-L. 2019;4(3):2539–2546.
140. Gorissen B, Melancon D, Vasios N, Torbati M, Bertoldi K. Inflatable soft jumper inspired by shell snapping. Sci Robot. 2020;5(42):1–8.
141. Tang Y, Chi Y, Sun J, Huang TH, Maghsoudi OH, Spence A, Zhao J, Su H, Yin J. Leveraging elastic instabilities for amplified performance: Spine-inspired high-speed and high-force soft robots. Sci Adv. 2020 ;6(19).
142. Li Z, Huang Z, He W, Su C-Y. Adaptive impedance control for an upper limb robotic exoskeleton using biological signals. IEEE Trans Ind Electron. 2016;64(2):1664–1674.
143. Chen X, Li G, Wei L, Yeh S-C, Xu LD, Zheng L, Zou Z. A wearable hand rehabilitation system with soft gloves. IEEE Trans Industr Inform. 2020b;17(2):943–952.
144. Santina CD, Bianchi M, Grioli G, Angelini F, Catalano M, Garabini M, Bicchi A. Controlling soft robots: balancing feedback and feedforward elements. IEEE Robot Autom Mag. 2017;24(3):75–83.