Emerging Wearable Interfaces and Algorithms for Hand Gesture Recognition: A Survey

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***Abstract*—Hands are vital in a wide range of fundamental daily activities, and neurological diseases that impede hand function can significantly affect quality of life. Wearable hand gesture interfaces hold promise to restore and assist hand function and to enhance human-human and human-computer communication. The purpose of this review is to synthesize current novel sensing interfaces and algorithms for hand gesture recognition, and the scope of applications covers rehabilitation, prosthesis control, exoskeletons for augmentation, sign language recognition, human-computer interaction, and user authentication. Results showed that electrical, mechanical, acoustical/vibratory, and optical sensing were the primary input modalities in gesture recognition interfaces. Two categories of algorithms were identified: 1) classification algorithms for predefined, fixed hand poses and 2) regression algorithms for continuous finger and wrist joint angles. Conventional machine learning algorithms, including linear discriminant analysis, support vector machines, random forests, and non-negative matrix factorization, have been widely used for a variety of gesture recognition applications, and deep learning algorithms have more recently been applied to further facilitate the complex relationship between sensor signals and multi-articulated hand postures. Future research should focus on increasing recognition accuracy with larger hand gesture datasets, improving reliability and robustness for daily use outside of the laboratory, and developing softer, less obtrusive interfaces.**

***Index Terms*—Rehabilitation, human-computer interaction, machine learning, electromyography, forcemyography.**

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I. Introduction

HANDS are essential for performing daily activities including grabbing a cup or conveying information to others, such as waving goodbye. As the global population ages, the incidence of neurological diseases is causing increasing loss of hand function leading to decreased quality of life [1], [2]. Automated hand gesture recognition can be integrated with games to help assess rehabilitation progress with active engagement [3] or combined with orthoses [4] to support grasp strength. Similarly, upper extremity amputees often retain intention and neural motor control [5], and gesture recognition interfaces can decode human intention commands for prosthesis manipulation movement control [6] or grasping force control [7], enabling independent living. These hand gesture recognition interfaces not only enable home-based daily activity but also ease the load of specialized clinicians in hospitals.

Hands are the primary form of communication for the hearing impaired [8], and hand gesture recognition interfaces can enable communication with the unimpaired via automatic sign language translation [9]. Hand gesture recognition has also shown potential to provide more intuitive communication for a variety of emerging human-computer interaction applications [10], including gesture interaction with smartphones [11], virtual reality (VR)/augmented reality (AR) [12], and in-vehicle menu control to avoid visually searching for control while driving [13]. New materials, novel sensing techniques, and miniaturization of embedded systems can enable more intuitive and comfortable wearable interfaces, while the advances in machine learning algorithms hold promise for more accurate, powerful, and robust classification and tracking performance.

Algorithm capability for hand gesture recognition has improved significantly in recent years. Previous approaches based on simple threshold control or fuzzy logic primarily rely on human knowledge; in contrast machine learning has become more dominant in recent years, including statistical learning approaches like expectation maximization and maximum a posteriori [14]. Deep learning techniques [15], widely for image classification, include convolutional neural networks (CNN) [16], transfer learning [17], and meta learning [18] are also emerging in hand gesture recognition applications to improve the performance and solve biological difference problems without relying on apriori knowledge.

The purpose of this review is to comprehensively analyze the array of recent novel wearable interfaces and algorithms for

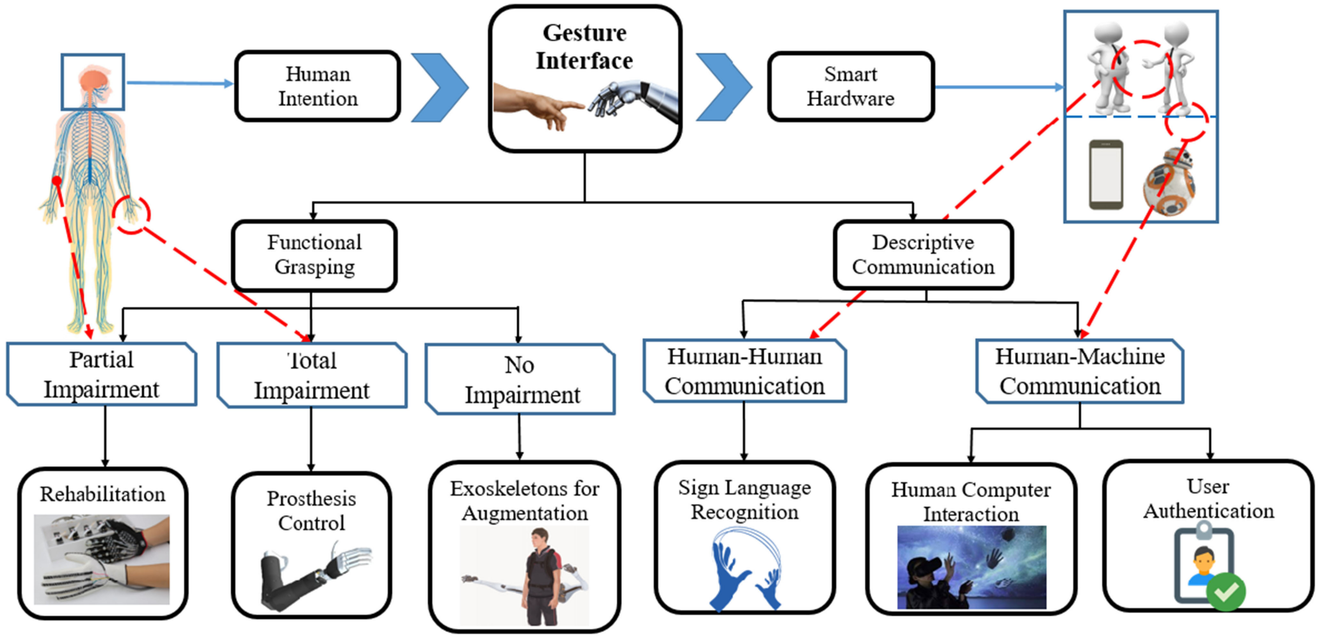

Fig. 1. Wearable hand gesture interfaces connect human intention with smart hardware to facilitate functional grasping and descriptive communication for a variety of applications, including rehabilitation, prosthesis control, exoskeletons for augmentation [21],sign language recognition, human-computer interaction, and user authentication.

hand gesture recognition and to identify existing challenges that currently hinder practical use. Selected papers used wearable sensing methods attached to the human body at one or more of the following locations: upper limb, wrist, back of the hands, and fingers. Hand gesture and/or pose tracking was required to perform at least one of the following: classify static gesture categories, estimate dynamic finger flexing angles, or classify hand movement trajectories. Articles based on computer vision methods or based on data gloves for hand gesture recognition were excluded as these have been the topic of recent reviews [8], [19], [20]. In Section II, we provide an overview of applications of wearable hand gesture recognition based on hand function. Section III describes categories of interfaces and sensing principles with a discussion of their advantages and limitations. In Section IV, we introduce conventional and emerging novel decoding algorithms, and finally, in Section V, we present potential research directions for hand gesture recognition.

II. Scope of Applications

There are two general purposes of hand gestures: functional grasping and descriptive communication. Wearable interfaces can be utilized for gesture recognition in both areas to bridge the gap between human intention and human-machine or human-human communication (Fig. 1). This can both improve quality of life and enable more intuitive interaction. Generally, humans freely move their hands and fingers to perform functional movements or to convey information. However, in some cases, the transmission of intention is obstructed, or the expression is degraded by keyboards due to hardware limitations for more direct and intuitive expression. In addition, hand gestures typically involve coordinated movement of all 5 fingers and are often relatively complex, consisting of one or more combinations of the following: finger flexion/extension, finger abduction/adduction, wrist pronation/supination, wrist radial/ulnar deviation, wrist flexion/extension, forearm pronation/supination, and hand position translations. In many applications, it is unrealistic and unnecessary to capture and classify every possible hand and finger pose, and instead defining a target hand gesture set can enable adequate performance for a given specific application. The following sections introduce the major applications of wearable hand gesture interfaces and the corresponding gesture sets.

For functional grasping, rehabilitation is used for severe stroke patients and others who partially lose motor function and need an exoskeleton to help them carry out daily activities or for rehabilitation. There are prosthesis/exoskeleton controls for amputee patients with total motor function loss to assist with daily living, and for able-bodied group for augmentation including workload reduction. Sign language recognition is used for human-human communication, and intuitive human computer interaction (HCI) is used to enable humans to communicate with smart hardware while user authentication can also be achieved via hand gesture related signals to ensure the security during communication.

A. Rehabilitation

Neurological diseases, such as stroke and cerebral palsy, spinal cord injuries, and brachial plexus injuries can cause long-term motor function impairment [22], [23]. Hand motor function is closely related to activities of daily livings (ADLs), which significantly impacts quality of life [24]. Thus, patients with hand motor dysfunction need effective rehabilitation, which should be goal-oriented, intensive, and repetitive [25]. Conventional rehabilitation relies heavily on the guidance and assistance of clinicians and physiotherapists, which is labor-intensive and expensive. Thus, rehabilitation can impose a significant burden on clinicians, physiotherapists and patients. In addition, it is difficult for discharged patients to persist in effective home-based rehabilitation due to repetitive, uninteresting rehabilitation protocols in unsupervised environments [26]. To overcome these problems, many studies have focused on the development of wearable systems for hand function rehabilitation [1], [2]. For patients with neurological diseases, although hands movements are partially inhibited from brain intention, existing neural information can be detected through wearable interfaces. The detected information can reflect rehabilitation stages for assessment or help to enable exoskeleton to assist ADLs. There are two main methods for this: unassisted rehabilitation systems for patients with moderate to high hand function and assisted active rehabilitation for moderate- to low-functioning patients as described below.

1) Unassisted Training: For patients with moderate to high function, unassisted training is best for rehabilitation because it maximizes neurological restoration [27]. Therefore, some movement-classification-based unassisted wearable sensing systems have been developed to guide patients to perform goal-oriented movements via serious games, which could optimize patient engagement [28]. By attaching one accelerometer on the back of hands and three surface electromyography (sEMG) sensors around the forearm, a game-based upper limb rehabilitation program was developed for children with cerebral palsy. The accelerometer was used to detect the rotation of the tracking wrist, and sEMG was used to detect the flexion and extension of the fingers [29]. In addition, an inertial measurement unit (IMU) attached to the wrist has been used to measure the rehabilitation progress and encourage patients to use their affected hand by monitoring ADLs continuously in both clinical and non-clinical scenarios; three tasks involving forearm extension/flexion and rotation were classified by a lightweight CNN [30]. IMUs have also been attached to the wrists to monitor stroke patient ADLs and encourage the use of affected limbs to perform more goal-oriented tasks. Goal-directed and non-goal-directed movements were classified by logistic regression [31].

2) Assisted Training: For patients with low to moderate mobility, robot-assisted active training could increase patient compliance to be involved in rehabilitation and be more effective than passive training [32], [33]. Thus, pattern recognition techniques are critical for a robotics-based system to provide accurate motion control. sEMG and IMUs have been used to detect motor intention. Many robotics-based systems provide bilateral grasp rehabilitation, which use muscle sEMG of the unaffected hand and forearm for classification and trigger the execution to drive the affected limbs of the patients for rehabilitation training [34], [35]. Other studies have focused on intention detection based on sEMG signals from the affected side of stroke patients [36]–[38]. However, the sEMG-based classification results of movement intentions of stroke survivors are less accurate than those of healthy people due to neural damage.

B. Prosthesis Control

For upper extremity amputees, there often still exist neural signals in the residual limb, and decoding these neural signals can reflect the human intention for hand gestures which is crucial for intuitive prosthesis control. This can solve daily-living problems, including drinking water and grabbing objects without the help of caregivers. Since amputees have lost their hands, traditional vision-based methods cannot decode their intentions, and current commercially available prostheses are mainly based on on-off control that is cumbersome and has only simple open-loop functions. In this case, wearable interfaces can act as an intuitive way to decode amputees' gesture intentions for controlling the robotic prosthesis with more degrees of freedom (DoFs). The wearable interface is the key to realizing closed-loop functional control which is the trend in cutting-edge research [39]. They can help realize continuous control of a prosthesis finger angle, or with continuous force level control (also referred as proportional control), enable more dexterous control of a prosthesis and provide a better experience in their daily lives. Currently, the wearable interface is dominant in prosthesis control areas and is mostly realized through neural signals, including sEMG [5] or the partial force/deformation information in the patients' residual arms. In this prosthesis control application, the target gesture-controlling commands not only contain visible information like position/angle but also deal with invisible information, including torque and force. Most of the target gestures are motivated by prosthesis capabilities for daily grasping activities [40]. Thus, based on the scenarios and requirements, many researchers define their own target gestures and develop their own datasets, which may make direct and fair comparison across different research difficult, and thus cause confusion for new researchers. Fortunately, there are still some popular open datasets, which not only serve as good examples for experimental protocol design on the application side but also offer good avenues for researchers who focus on the algorithm side. Popular public open datasets include NinaPro [41], CSL-HDEMG [42], and CapMyo [43]. A detailed summary and descriptions of these datasets can be found in [44].

Like amputees, some stroke patients' motor function impairments are too severe to restore, which may cause lifelong disability. These patients need assistive devices to help with accomplishing ADLs [25]. Compared to rehabilitation systems, these daily assistive devices are more like prostheses, and more integral to the patient's daily life [24]. Therefore, the detection of reach and grasp intention becomes the key point in the related research. A light, wearable soft-robotic orthosis was developed to support ADLs. IMUs were placed on the back of the hand, ulnar styloid, and phalanges of fingers to classify the reach and grasp intention and to detect the grasp intention as soon as possible. This then triggered the orthosis to support the patient's grip strength [4]. Forearm sEMG-based intention detection has also been employed to control assistive exoskeletons or hand prostheses [45]. Most of the movements were selected from clinical-based assessment scales, and are highly related to ADLs, including wrist flexion, wrist extension, mass flexion, mass extension, hook-like grasp, opposition (hand pinch) and thumb adduction (lateral hand pinch), cylinder grip, and spherical grip [36]–[38], [46].

C. Exoskeletons for Augmentation

Although the main application of exoskeletons is still in the rehabilitation of stroke patients, they can also act as an effective way to enhance able-bodied people's capability. Because hands are humankind's main manipulators, hand gesture recognition technology can be used for intuitive control of capability augmentation. The capability augmentation for an able-bodied group can be categorized into two aspects: strength augmentation and function augmentation. For strength augmentation, Al-Fahaam *et al.* [47] proposed an artificial muscles-based exoskeleton for decreasing workers' manual efforts in grasping objects. For function augmentation, supernumerary robotics, including extra arms [21], third hand, and extra fingers, can help extend the function of humanity and realize the vision of *Man-Computer Symbiosis* [48]. The future development of the hand exoskeletons should be focused on making lightweight, soft, low cost, high load capacity systems [49]–[51].

D. Sign Language Recognition

Gestures are the decoding of brain intention, and some simple and commonly used gestures, including the OK sign, can be easily and universally understood. However, for deaf and hearing impaired, sign language, is the primary means of communication and consists of complex gesture linguistics. However, the vast majority of the unimpaired population does not recognize sign language. Thus, a significant communication gap exists between the hearing impaired and a majority of the unimpaired population. Because sign language is frequently used by hearing impaired in daily living situations, computer vision based approaches are not suitable because of privacy concerns, sensitivity to lighting conditions, and higher energy consumption. In contrast, wearable interfaces can provide a ubiquitous and low-energy approach. Although data-glove-based systems can achieve an relatively high classification rates [52], they have not been widely adopted likely because they are too cumbersome for practical daily living use and are not suitable for natural human-computer interaction [9], [53], [54]. Other low-cost and ubiquitous wearable interfaces can serve as alternatives to data gloves. With the advances in material science, epidermal e-skin sensors provide similar principles for capturing fingers' bending angles but offer better user experiences including epidermal-iontronic sensing [55], and carbon nanotubes [56]. IMUs [57] are also a widely-adopted method for acquiring kinematic information for finger movements. sEMG shows advantages in monitoring muscular movements, and the commercial product MYO also made it popular at a low cost [58], [59]. In addition, Chen *et al.* [60] proposed using a camera on the wrist to sense the background changes and infer hand movements. Notably, a hybrid method of the above sensing technologies including sEMG provides a good solution. For example, Chen *et al.* [9], [61], [62] proposed a framework for sign language recognition based on the information fusion of a three-axis accelerometer and multi-channel sEMG modeling the sign language into basic kinematic components, including hand shape, orientation, rotation, and trajectory. This framework was also adopted by Wu *et al.* [63] for American sign language recognition. This topic has gained increasing attention and was reviewed recently by Kudrinko [64]. In this application, the most basic target gesture sets were the 10 American digits [65] and 26 American sign language letters [66]. Higher target gesture sets are subwords [54], words [62], [63], and sentences [61].

E. Human Computer Interaction

One important aspect in consumer electronics is gesture-based human-computer interaction, which is an intuitive way of expressing user ideas that can enhance the understanding between humans and smart devices. Recent advances in VR/AR technologies have increased demands for more natural and immersive interaction between users and the devices. Since vision-based hand gesture recognition has some inherent defects like no haptic feedback, targets out of camera view, and occlusion, wearable interfaces can not only overcome the occlusion problem from a sensing perspective but also can be combined with haptic feedback to form a closed-loop immersive experience. However, currently, most available commercial VR sets are composed of a head-mounted display, two controllers, and a base station [67] and can only recognize 6-DoFs movements base on IMUs or cameras. However, the newest VR games require finger movement recognition, and only a few leading products such as the Oculus Touch and Valve Index can recognize a handful of simple finger movements like shooting and grabbing. Compared to the conventional joystick input device, hand gesture control is intuitive, relatively easy to learn and use [68]. Examples of commercial hand gesture recognition devices in VR/AR applications include Knuckles controllers (controllers for the Valve Index) and MYO armbands (sEMG armband).

Smartwatches are another emerging field to apply hand gesture recognition technology. Since smartwatch screens are too small for many touch-based gestures, hand gestures for operation or typing are a potential alternative. However, popular hand gesture recognition methods, including sEMG and forcemyography (FMG), require extra components and a large space, which most smartwatches cannot accommodate. Some novel research has reported hand gesture recognition methods without extra components, using existing smartwatch sensors including photoplethysmography (PPG) [69], microphones [70], and bone-conducted sound sensing [71].

F. User Authentication

Privacy and security are important issues during communication process. Recently biometric passwords based on face and iris have been applied in real-life scenario while other novel biometrics-based modalities including EEG [72], gait [73] have gained increasingly popularity in research area. Due to the individual uniqueness of biological signals, hand gestures can also be used as passwords for electronic equipment (user authentication/identification). For wearable devices, current research mainly focuses on sEMG signals [74], [75]; other sensing modalities like electrical impedance tomography (EIT) [76] and

TABLE I
SENSING METHODOLOGIES

Sensing Modality	Sensing Principle	Measured Biological Characteristics	Wrist	Arm	Back of Hand	Fingers
Electromyography(EMG)	Electrical	Electrical Activity	[10], [78]	[6], [9], [79], [80]	[81]	
Electrical Impedance Tomography(EIT)	Electrical	Skin Impedance	[82], [83]	[76], [82], [84]–[86]		
Electrical Contact Resistance Sensing	Electrical	Deformation of Skin	[87]			
Capacitance Sensing	Electrical	Deformation of Skin	[88]–[90]	[91]		[55]
Forcemyography(FMG)	Mechanical	Force of Muscles or Tendons	[78], [92]–[97]	[98]–[102]		
Inertial Measurement Unit(IMU)	Mechanical	Movement	[10], [103]–[105]			[106], [107]
Strain Sensing	Mechanical	Deformation of Hand or Fingers	[108]		[65], [108]–[112]	[108]–[110], [113], [114]
Flex Sensor	Mechanical	Flexion of Fingers				[115]–[118]
Ultrasound Imaging(A-mode)	Acoustical/Vibratory	Myoarchitecture		[119]–[121]		
Ultrasound Imaging(B-mode)	Acoustical/Vibratory	Myoarchitecture		[122]–[125]		
Mechanomyography(MMG)	Acoustical/Vibratory	Vibration of Muscle Fibers	[70], [104], [126]	[127], [128]		
Bone-Conducted Sound Sensing	Acoustical/Vibratory	Spectrum of Active Vibration	[71], [129], [130]	[131]	[132]	[130], [133]
Near-Infrared Spectroscopy(NIRS)	Optical	Vascular Deformation	[134], [135]			
Photoplethysmography(PPG)	Optical	Vascular Deformation	[69], [136], [137]			
Time of Flight(ToF)	Optical	Deformation of Skin	[138], [139]	[140], [141]	[142]	
Optical Fiber FMG	Optical	Force of Forearm		[143], [144]		

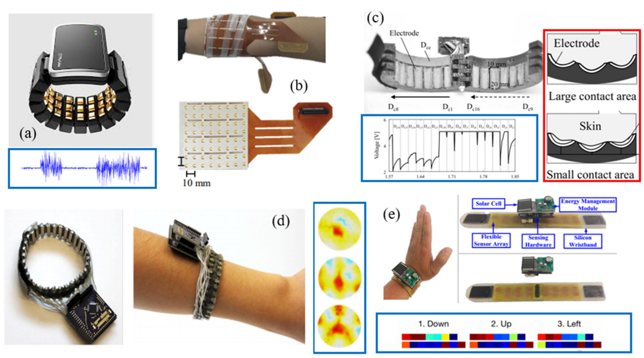

Fig. 2. Representative electrical sensing approaches: (a) sEMG armband developed by CTRL-Labs [145], (b) high-density sEMG [80], (c) electrical-contact-resistance-sensing [87], (d) EIT [84], (e) capacitance-sensing [89].

IMU [77] also have the potential to be used for user identification. With the development and popularization of wearable devices, wearable user authentication/identification methods will get more attention from both equipment suppliers and consumers.

III. Sensing Modalities

Hand gesture changes are caused by muscle contractions and tendon slippage in the arm and wrist and are accompanied by blood vessel deformation and bone movement. During hand and finger movements, many biological and physical characteristics change. These changes can be captured by electrical, mechanical, acoustical/vibratory, or optical sensing methods and used as input for classification and regression algorithms. In this section, each of these types of sensing principles is introduced along with representative sensing modalities, measured biological characteristics, and interface locations (Table I).

A. Electrical Sensing

Muscle contraction is triggered by electrical signals and leads to impedance distribution changes (Fig. 2). These electrical signals and impedance distributions can be recorded by sEMG and EIT. Due to the high information transmission rate and high time resolution, sEMG is the most extensive and in-depth investigated method in wearable hand gesture recognition. sEMG monitors and records the change in electrical signals through electrodes placed on the skin or inside the muscle tissue. It contains important information about muscle contraction, which drives hand movement. There are mainly three different layouts of sEMG: muscle-targeted layout (placing one sEMG sensor on each specific muscle to monitor its contraction [9]), low-density surface electrode layout (assembling several sEMG sensors in a wristband or a sleeve to recognition gestures or motion [6], [10]) and high-density electrode layout (using dozens of closely spaced electrodes to collect sEMG signals in an area [79]). The current and potential application of the sEMG method includes prosthetic control [146], game or computer controls (MYO wristband), user authentication [74], [75]. The advantage of the sEMG method is that it is neuromuscular measurement and contains abundant and fundamental information about muscle contraction. Also, as one of the most used gesture recognition methods, numerous commercial sEMG acquisition devices including Delsys and Biometrics can provide quick and stable measurement and various algorithms have been extensively explored. The disadvantage of the sEMG method is that sEMG has some inherent defects like subject dependency and non-stationarity [147], [148]. Also, in real-application, the sEMG will introduce interference due to muscle fatigue and skin sweat [149].

EIT is a non-invasive tomographic method widely applied in medical applications. Human body tissue has electrical impedance, which varies with the structure of the body and can be monitored by surface electrodes on the skin [150]. Based on this, Yang *et al.* [82] proposed a prototype using the EIT method to recognize hand gestures. The EIT method is highly subject-dependent. The current and potential application of the EIT method also includes user authentication [83]. The advantage of the EIT method is that it has a high recognition accuracy in discriminating gestures with similar muscle contraction [76], [85]. The disadvantage of the EIT method is that EIT is highly sensitive to environmental interference (a fluorescent light ballast will cause persistent electromagnetic interference) and can impede contact with the skin [82].

Some hand gestures could lead to skin deformation, which can also be used as a feature to recognize hand gestures. There are

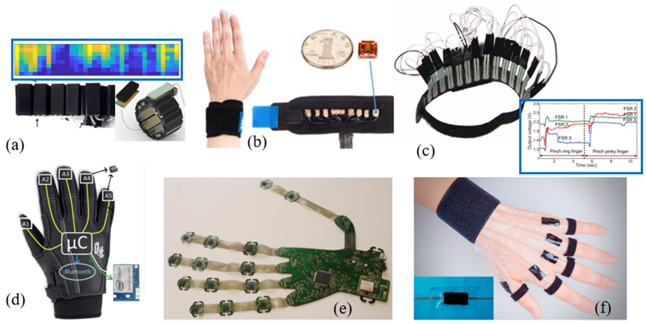

Fig. 3. Representative mechanical sensing approaches: (a-c) FMG [94], [96], [102], (d, e) IMU [106], [107], (f) strain sensor [111].

two types of electrical sensing methods that can capture this deformation: electrical contact resistance sensing and capacitance sensing. Electrical contact resistance is dependent on contact shape, dimensions, and the magnitude of the mechanical contact load [151]. Kawaguchi *et al.* [87] proposed an electrical-contact-resistance-sensing hand gesture recognition method that utilized the corresponding dependence of the resistance to detect skin deformation to recognize hand gestures. The current or potential application of the electrical contact resistance method includes finger joint angle estimation [87]. The advantage of the electrical contact resistance method is that it is lightweight (0.067 kg) and comfortable (does not need strong contact pressure), making the device acceptable to users. The disadvantage of the electrical contact resistance method is that it will be seriously interfered by irrelevant movements of the wrist, elbow, and forearm [87]. Capacitance sensing is an electrical sensing method built on the principle that skin deformation will cause the distance between two electrodes (which are attached to the skin or, in some cases, skin also serves as an electrode) to change and results in a change in capacitance [88]. The current or potential application of capacitance sensing includes game control, sign language translation, and object control [89]. The advantage of capacitance sensing is that it is ultra-low power and does not require re-training before each use [89]. The disadvantage of capacitance sensing is that the sensing performance may be interfered with by temperature, humidity, and skin condition change. Also, after long-term usage, the electrode can be contaminated by the skin, which will lead to a decreases capacitive value [55].

B. Mechanical Sensing

Mechanical sensing can be divided into four types: FMG, inertial measurement sensing, strain sensing and flex sensor sensing (Fig. 3). FMG is the record of muscle activity in the force domain and can be measured from the local pressure change at the sensor location. Force-sensitive resistors are the most commonly used method [92], [152]. In addition, force sensors can also be an air-pressure sensor encapsulated in an air-bladder [98] or covered with an elastic rubber (TakkStrip, TakkTile, USA). FMG sensors usually have a wristband-like layout to recognize hand gestures or finger flexion angleds [95], [96]. The current or potential application also includes prosthetic control [153]. The advantage of the FMG method is that compared with sEMG, the FMG has a better performance in classification/regression and has been subjectively preferred by users [153]. Also, FMG will not suffer from skin condition change as sEMG does. The disadvantage of the FMG method is that each FMG sensor needs an appropriate initial pressure, which means that the user has to adjust the wristband carefully to avoid it becoming too tight (causing an over-range error) or too loose (causing a bad contact error). In prosthetic control, this means that the FMG sensor array needs to be customized according to the shape of the residual limb. Additionally, force-sensitive resistors also have drift problems and are vulnerable to electromagnetic interference problems [154].

Inertial measurement sensing is a kinematic sensing method, take the IMU as an example, an IMU consists of a 3-axis accelerometer, a 3-axis gyroscope, and sometimes a 3-axis magnetometer. The current or potential application of the IMU method contains two primary layouts: put one IMU on each hand movement's DoF [106] or use a single IMU as a part of the sensor fusion system to help deal with dynamic hand gestures [10]. Additionally, an IMU's components can also be used separately (e.g., magnetic sensors can be put on fingers to monitor finger movement and serve as a handwriting input device [155]). The advantage of the IMU method is that it is sensitive and generally achieves a high accuracy in dynamic hand gesture recognition. Also, the IMU sensor is cheap, easy to use. If the subject performs hand gestures according to one standard protocol, the IMU signal will have almost no individual difference. The recognition accuracy of IMUs is largely dependent on the wearing position of the sensor. When performing the same hand gesture, different body positions (e.g., fingers, wrist, forearm) will have significantly different kinematics characteristics, which may result in a different systematic accuracy. In addition, due to loose wearing conditions and long-time use, sensor shifting may also cause differences in training and testing data, thus resulting in reduced recognition accuracy. The disadvantage of the IMU method is that the IMU-based hand gesture recognition method is easily interfered with by human body motion including waving the arm and walking.

Strain sensors are typically attached to the skin of the fingers and hand. Since the strain sensor is tightly attached to the skin, any finger or hand movement will cause the reading of the strain sensor to change, and thus the hand gesture can be recognized. An ideal strain sensor would be cheap, invisible, thin, lightweight, stretchable, and easily attachable to the skin [111]. The potential application includes smart gloves. The advantage of strain sensors is that they usually have higher resolution [111] and higher robustness (not susceptible to electrode shift and electronic interference from the environment) [65]. The disadvantage of strain sensors is that due to the limitations of materials and fabrication, these features (cheap, invisible, thin, lightweight, stretchable, and attachable) usually cannot be achieved simultaneously and thus hinder practical adoption. In addition, strain sensors sometimes have liquid leaking problems [109], poor stability (sensing characteristics can change as the number of uses increase) [111], [156], short service life (only weeks) [110], [157], and mass-production problems [109].

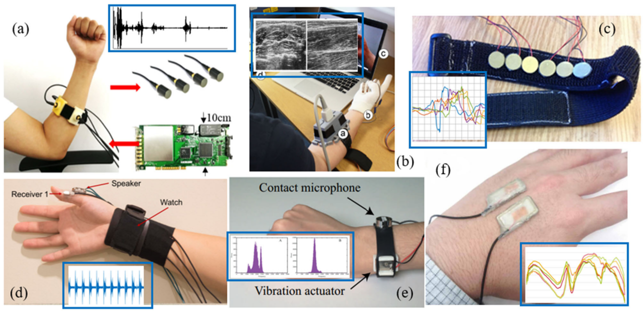

Fig. 4. Representative acoustical/vibratory sensing approaches: (a) ultrasound imaging (A-mode) [119], (b) ultrasound imaging (B-mode) [123], (c) MMG [126], (d-f) bone-conducted sound sensing [71], [130], [132].

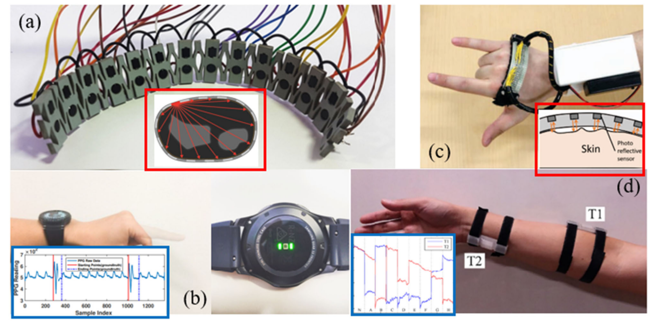

Fig. 5. Representative optical sensing approaches: (a) NIRS [135], (b) PPG [136], (c) ToF [142], (d) optical fiber FMG [144].

A flex sensor is a thin strip-like resistor that can be used to measure the angle of bending, and different angles will cause different levels of resistance. Flex sensors are usually embedded in a smart glove with a flex sensor corresponding to each finger [116]–[118]. One potential application reported by Jani *et al.* [117] is sign language translation. The advantage of the flex sensor is that it is cheap, easy to manufacture, and easy to use. The disadvantage of the flex sensor is that its angle measurement accuracy is relatively low.

C. Acoustical/Vibratory Sensing

The physical structure of the wrist and forearm change will cause different echoed acoustic characteristics generated by the outer source equipment or the muscle itself, and thus acoustical sensors can be used in hand gesture recognition. Currently, there are three main acoustical sensing methods: ultrasound imaging, mechanomyography, and bone-conducted sound sensing (Fig. 4). Ultrasound imaging can be used to detect morphological changes in muscles with high spatial and temporal resolution [125], [158]. There are two kinds of ultrasound imaging: A-mode (portable, one-dimensional sonomyography) [119] and B-mode (high-resolution, two-dimensional sonomyography) [125]. Since both the superficial and deep muscles control human hand motion, and unlike sEMG, ultrasound can capture deep muscle activity and superficial muscle activity simultaneously. The advantage of the ultrasound method is that it has a higher spatial resolution and recognition accuracy [125], [159], [160]. The disadvantage of the ultrasound method is that the devices are usually bulky and expensive, power-consuming, and require a coupling medium [123].

Finger or hand movement will cause the wrist geometry structure to change and generate vibration [161], which can also be regarded as sounds to some extent [128]. Mechanomyography (MMG) is a record of low-frequency vibration made by skeletal muscle [162], which is highly related to muscle contraction and hand movement. MMG can be recorded by accelerometer [163] (the accelerometer is used to measure vibration), microphones [70], [164], and piezoelectric sensors [165]. The advantage of the MMG method is that it does not suffer from the skin condition like sweat and can serve as a supplement to the sEMG [149]. The disadvantage of the MMG method is that it has motion artifacts and a low signal-to-noise ratio, and it often experiences interference from background noise [166], [167].

Bone-conducted sound sensing is an active-vibration-based hand gesture recognition method. Unlike MMG, bone-conducted sound sensing needs an active vibration source rather than merely measuring the sounds and vibrations intrinsically generated by muscle structural deformation. Bone-conducted sound sensing consists of a contact receiver (microphones or piezoelectrics) and vibration actuators. Morphological changes of muscles will affect the spread of the active vibration and will cause the received vibration's characteristics, including amplitude [129], [131], [133] and power spectral density [71], to change. The advantage of bone-conducted sound sensing is that by using an unnoticeable vibration (which enables sensing) and a noticeable vibration (which provides haptic feedback) simultaneously [133], bone-conducted sound sensing can achieve an immersive configuration of human-computer interaction more easily. The disadvantage of bone-conducted sound sensing is that the generated sound can be heard by humans and thus becomes noise and annoying.

D. Optical Sensing

Optical sensing is lightweight, portable, and easy to integrate into consumer electronics such as a smartwatch (Fig. 5). The most representative sensing method for optical sensing is PPG. A PPG sensor is a common optical sensor that can be seen on the back of nearly every smartwatch and is used to monitor pulse rate. The PPG sensor is made of an LED (light-emitting diode) to generate light and a light intensity sensor to monitor reflected light. The light that comes from the LED will be absorbed by the blood in the blood vessel, and thus the larger the blood vessel, the more light it absorbs and the less it reflects. Zhao *et al.* [69] found that hand movement would compress the arterial geometry and cause significant motion artifacts to the blood flow. These motion artifacts can be monitored by the PPG sensor, and the gesture-related signals can be extracted from it [136]. The potential application of the PPG method is that it can be used as a low-cost fine-gained gesture recognition method on the commercial smartwatch. One great advantage of the PPG method is that it is cheap, lightweight, and commonly installed on a smartwatch.

Other optical sensing methods can also be used in hand gesture recognition. For example, muscle contraction leads to variations in speckle field intensities, and these variations can be monitored by an optical fiber specklegram sensor. Wu *et al.* [144] used this phenomenon to develop a hand gesture recognition system. Based on the same theory, optical sensors used in other fields can also be used for hand gesture recognition if they can capture hand-gesture-related characteristics. Near-infrared spectroscopy (NIRS) is a commonly used chemical component analysis method for ambulatory monitoring of tissue oxygenation and haemodynamics [168]. Hand gesture changes lead to vascular deformation and cause hemodynamics variations, and thus, they can be captured by the near-infrared sensor and recognized by NIRS analysis [134]. A time-of-flight (ToF) sensor is another commonly used optical sensor to measure distance, and it was previously used to measure the depth information of an image. Since the muscles and bones are linked to the skin, hand gestures cause skin deformation [142]. By measuring the distance between the skin and the sensor, the skin deformation can be determined, and thus, the hand gesture can be estimated [140]. Note that several research studies [138]–[140] using near-infrared sensors were categorized as ToF method in this paper because these studies merely used near-infrared sensors to measure distance, rather than analyzing the optical characteristics of infrared light scattered by human tissue.

These methods are new to hand gesture recognition and lack further research. However, these optical sensing methods have several common drawbacks, including susceptibility to the interference of ambient light noise [135] and high sensitivity to sensor location (thus, they must be re-calibrated before every use), skin condition, and intense body movement(e.g.,coughing) [112], [137], [144]. These drawbacks make the optical sensing methods hard to maintain recognition accuracy in practical applications. However, optical sensors are often compact and easy to be integrated into consumer electronics, making optical sensing an ideal potential solution for commercial wearable hand gesture recognition.

E. Comparison

For a better understanding of the advantages and the disadvantages of these sensing modalities, this paragraph gives a brief comparison of the above sensing modalities. The comparison will be conducted on three aspects: sensitivity, wearability, and maturity. For sensitivity, the sEMG (electrical), EIT (electrical), FMG (mechanical), ultrasound imaging (acoustical), NIRS (optical), and PPG (optical) methods directly measure the muscular movement and thus have a high sensitivity and resolution. The sensitivity of the IMU and strain sensing method depend on the device setup. For IMUs, sensors placed on finger segments will have a high sensitivity to hand gestures, but sensors placed on the wrist will not. For strain sensing, it depends on the used materials and can vary greatly. Methods that measure the skin deformation (electrical contact resistance sensing, capacitance sensing, ToF) or have a low signal-to-noise ratio (MMG, bone-conducted sound sensing) are usually less sensitive. For wearability, the optical sensing methods usually have the smallest size and can easily be integrated into commercial devices. The electrical methods, FMG, MMG, and bone-conducted sound sensing can be made into wristband types, which is also acceptable to commercial devices. The strain sensing, flex sensor, and glove-layout IMU sensors are usually made into a glove shape; this can be acceptable for patients and industrial applications but hard for consumers to use. The ultrasound imaging method has the lowest wearability; although the ultrasonic probes and processing circuits are becoming smaller, it still needs a coupling medium. For maturity, methods including sEMG, FMG, IMUs, flex sensor, and ultrasound imaging have lots of research and commercial devices, which will make it easier for the researcher to conduct experiments. However, other methods like electrical contact resistance sensing, capacitance sensing, strain sensing, MMG, bone-conducted sound sensing, and optical fiber FMG are only at the proof-of-concept stage. Other sensing modalities like EIT, NIRS, PPG, and ToF have mature applications in other areas, but applications for hand gesture recognition have just begun.

IV. Algorithms

Hand gesture recognition algorithms can generally be categorized as solving the problem of either classification of hand poses/trajectories (e.g. whether the hand is gesturing the OK sign or the hand is moving in a cycle form) or regression of a continuous parameter (e.g., continuous finger flexion angles or continuous wrist deviation angles). Generally, algorithms can be divided into two types: conventional pattern recognition and deep learning techniques (Fig. 6).

A. Conventional Machine Learning

Conventional techniques for classification and regression use a raw signal, handcrafted feature extraction, model training, and testing schemes.

Data pre-processing, which can include filtering, normalization, and window segmentation, is optional between the raw signal and feature extraction procedures. For example, for human sEMG signals, the effective spectrum is typically 20-500 Hz, and thus, a bandpass filter together with a notch filter is applied to remove low frequency drifting or power line noise. Normalization is used to make the range of raw signals the same scale, which can generally accelerate the training process. There are two kinds of normalization: min-max normalization, which maps the features to a certain range like $[-1, 1]$ to transfer the sensor values from different sensing modalities to the same scale, and z-score normalization, which transfers the features to similar distribution (with mean 0 and standard deviation 1) to shorten training convergence time. Window segmentation is commonly used to segment continuous data into basic analyzing units. All of the following procedures are then performed within the segmented window. For continuous processing of all the data, the segmented windows can slide across the time series data with an overlap, the length of which can influence the output frequency and the similarity within the adjacent windows.

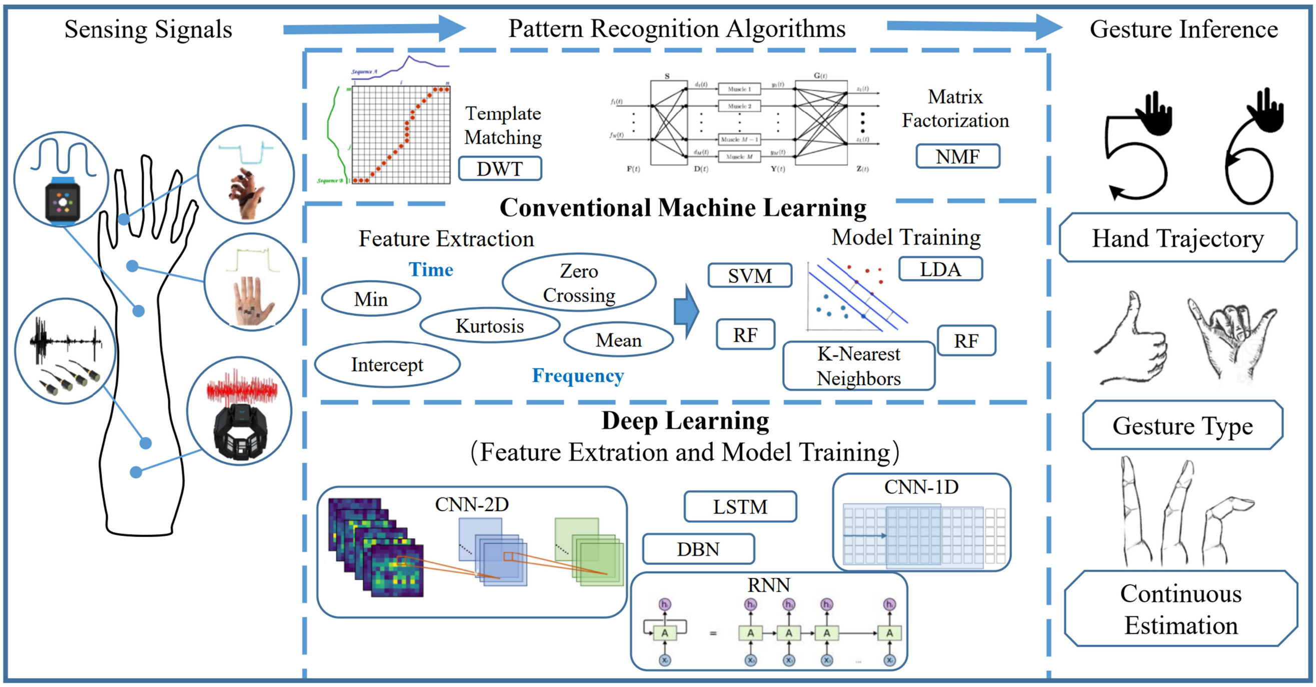

Fig. 6. Algorithms for hand gesture recognition and finger angle estimation. Sensing signals come from different wearable interfaces across various locations on the arm, hand, and fingers. Conventional machine learning and deep learning algorithms typically rely on feature extraction and model training to perform hand gesture pattern recognition. Ultrasound, soft sensing, finger IMU, and sEMG armband images come from [119], [65], [169], and [170], respectively.

Feature extraction is crucial for conventional pattern recognition. Generally, the features are handcrafted and can vary based on the source signal, usually covering time domain, frequency domain, or a combination of two. Features can be 1) statistics, including the mean, standard deviation, or kurtosis; 2) structural parameters, including the slope and intercept of the linear fitting [119]; or 3) task-specific, like zero crossings, waveform length, or slope sign changes for sEMG signals. The features are largely dependent on prior knowledge and have shown effectiveness in conventional application scenarios. Some research studies first chose as many features as possible and then applied a feature selection tool to optimize the feature sets and processing procedures [65], [104], [171]. Three different feature selection methods are commonly used: filter, wrapper, and embedded methods.

For classification tasks, model training involves classical machine learning schemes and usually includes linear discriminant analysis, support vector machines, random forests, multilayer perceptrons, naive Bayes classifiers, decision trees, k-nearest neighbors, and hidden Markov models. The no free lunch theorem indicates that there is no universal model suitable for all tasks and datasets. Thus, most researchers have tried several different algorithms [172] and selected a suitable one based on their requirements, including accuracy and computational expenses. In addition, parameter tuning is preferred to optimize the model for the tasks.

Various classification models can be modified to fulfill the regression tasks, including multiple regression [87], Gaussian process regression [121], support vector regressors [173], random forest regressors [96], and neural networks [94].

In addition, for dynamic gestures when the hand trajectory is used to circulate a number, because the performing times and signal lengths are different, dynamic time warping [174]–[177] is typically used to measure the similarity between a template and given sequence. For prosthesis control, a simultaneous and proportional algorithm can be achieved through non-negative matrix factorization in a semi unsupervised learning method [178]. Non-negative matrix factorization is applied in sEMG signals and motivated by muscle synergy theory. Raw signals from multiple channels of the interfaces can be factorized into muscle synergy matrix W, which reflects the weight for muscle involvement under a certain gesture, and matrix F, which reflects the activation level for each DoF. A short and simple calibration is needed for determining W, and F can be calculated for each DoF activation when in the training datasets. It is worth noting that this algorithm does not need force signals for training, only requiring the knowledge of which DoF is activated. As a result, simultaneous and proportional control signals for multiple DoFs can be achieved through semi-unsupervised learning.

B. Deep Learning

However, the handcrafted features cannot guarantee a global optimization and sometimes result in large performance variation based on different chosen features. Also, handcrafted features primarily rely on expert knowledge and often only extract shallow features, resulting in limited capability in fulfilling simple tasks. With the advancements in deep learning techniques, an increasing number of research studies use a convolutional neural network based solution. The flexibility in the neural network structure can enable the target output to be a classification problem, a regression problem [179], or a combination [180]. CNN has proved to outperform most conventional statistical-learning-based methods for image recognition problems and was initially designed for image classification or natural language processing [181], [182]. Therefore, directly adopting deep learning techniques in the field of wearable hand gesture recognition may not guarantee a better performance than conventional methods. The following factors should be considered when evaluating whether to adopt deep learning: 1) the volume of datasets, 2) the task complexity, 3) other demands (including robustness or few-shot learning) beyond the classification or regression accuracy, and 4) the expense of real-time computational expenses.

After the evaluation, gestures can change with time and the recorded signals from the interface also vary with time which can be processed by commonly used time-series processing procedure. Thus, 1D CNN [183] or recurrent neural networks, including long short-term memory (LSTM) [184], are often a suitable choice, and are quite common for a spatial-sparse signal source with limited channels (usually less than 10). For example, Panwar *et al.* [30] proposed an algorithm with two 1D-CNN layers for processing one IMU signal on the forearm and achieved 97.89% accuracy for 3 semi-naturalistic forearm movements. Zhu *et al.* [185] used bi-directional LSTM algorithm for decoding one IMU data from the smartwatch and successfully recognized 5 gestures with 96% accuracy. Kim *et al.* [186] recorded one IMU signals from a wearable band and then used the the architecture combining convolutional layers and gated recurrent unit (GRU) layers to recognize 9 arm gestures with 96.20% accuracy. However, these methods may neglect dependent relationships between dimensions and thus cannot fulfill challenging tasks [187].

Another solution is finding how to transform the low dimensional wearable sensor data into an appropriate form of high dimensional "image" data to seamlessly utilize the deep learning techniques. The answer varies based on the signal type, and the following parts introduce several representative explorations. One possible approach to expand the low dimensional data is to include longer time data to expand the image height. For example, in terms of the capacitance sensing, Khodabandelou *et al.* [90] used a 24-capacitance-sensor array and incorporated previous sequences to construct a 2D array. Then, an attention-based GRU neural network was utilized and realized 96% accuracy for 12 gestures. Similarly, Truong *et al.* [87] expanded the 15-channel data with a 4-second time frame, resulting in a 100×15 matrix, and then used CNN to realize a 0.95 F1-score for 15 gestures compared with 0.886 for random forest. Zakia *et al.* [188] proposed the FMG-based 2D-CNN algorithm to recognize 6 grasping gestures with 96% accuracy via a re-arranged data format to 16×25, which represented the sensor numbers and sampling window dimensions.

Another approach is to utilize the flexibility of the neural network for fusion with other sensing modalities. Yuan *et al.* [189] proposed using flex sensors for collecting bending angles, IMUs for arm postures, and CNN for feature extraction and fusion with LSTM to realize 99.93% for America signal language. A recent paper in Nature Electronics [56] also demonstrated that flex sensors can be combined with visual data via a fusion part in CNN with 96.7% accuracy in a dark environment. Kanokoda *et al.* [190] proposed using strain sensors and time delay neural networks (TDNN) to achieve 84.6% accuracy for three finger flexion/extension. Similarly, FMG can be combined with other sensing modalities. For example, Li *et al.* [191] proposed using a wrist-worn pressure sensor as an enhancer for ultra-wide-band doppler radar and a hierarchical classification model with the first stage classifier of SVM, resulting in 15% enhancement. Similarly, Liang *et al.* [192] also demonstrated that FMG can help to enhance the radar performance from 76.7% to 92.5% with 4 gestures via a multi-layer SVM data fusion algorithm.

For the relatively complex signal source like sEMG, which contains abundant information both in time domain and space domain, there are more advanced deep learning algorithms. For the time domain aspect, previous adding time dimension can also work for sEMG. Rehman *et al.* [193] utilized 150 ms eight-channel sEMG data to form a 30×8 image. For the space domain aspect, high density sEMG offers another dimension in constructing image. Geng *et al.* have performed extensive investigations on this direction based on transforming the high-density sEMG signals into an image. For instance, Geng *et al.* [43] directly transformed the 128 channel sEMG voltage at each sampled datum to an 8×16 instantaneous sEMG image and then applied a linear transformation to form a grayscale image covering the range of [0,1]. Furthermore, the 3D CNN structure could not only take an instantaneous sEMG image into consideration but also consider how the image evolves with time [194]. Also, Wei *et al.* proposed a multi-stream CNN [195], [196] which consisted of a decomposition stage to learn critical features and fusion stage for final recognition of gestures, achieving 95.4% accuracy in CSL-HDEMG dataset. Hu *et al.* [197] proposed an attention-based hybrid CNN-RNN algorithm and achieved 87% in the NinaPro dataset. Recently, Moin *et al.* [198] developed custom flexible sensor with 64 electrodes and a hyperdimensional computing algorithm which projected the sEMG data into hypervectors, achieving 13 gestures recognition with 97.12%. Xie *et al.* [199] compared the performance using deep learning methods including 1D CNN, LSTM, one convolutional layer and one recurrent layer (C-RNN) and found 3+3 C-RNN (3 convolutional layers and 3 recurrent layers) achieved the best performance over 3 datasets (eg. 83.61% for subdataset 5 of the Ninapro database).

In addition, there are also other deep learning methods which are different from convolutional neural networks. For example, Pan *et al.* [200] proposed using deep belief networks (DBN), and achieved 12 subtle gestures with 80.04% accuracy. The algorithm first used handcrafted features and then used a DBN which includes multi-layers of restricted Boltzmann machines (RBMs). Similarly, Yu *et al.* [201] also used a DBN and feature-level fusion strategy and achieved 95.1% accuracy for Chinese sign language recognition 150 subwords recognition. Apart from that, a deep-forest classifier, which is composed of decision tree and ensemble learning with cascade structure, is also used [201] and and has achieved 96% accuracy for 16 gestures.

V. Emerging Research Directions

A. Higher Accuracy for Larger Gesture Sets

Although the classification accuracy is high for certain applications, the total number of gestures tend to be limited [10], [71], [92], [98]. However, the limited gesture sets cannot realize various and intuitive control of hands as the hand is dexterous, not only possessing 21 DoFs for fingers but also showing 3 DoFs translation and 3 DoFs rotation in the wrist. Realizing high accuracy when the number of gestures increases is challenging because the hand structure is compact with 3D morphological structure and placing the sensor on a certain spot cannot fully detect the underlying changes especially for some similar like the letter U and V in American sign language. To increase gesture sets while maintaining high accuracy, the following are worth investigating. 1) Finding more powerful sensing techniques could help increase capability. For example, the ultrasound mode B, previously used in medical imaging areas, was recently investigated by McIntosh *et al.* [123] to realize 99% accuracy for static hand poses recognition via the musculature changes in real time. In addition, high-density sEMG sensors are powerful in investigating the physiological process of muscle contraction [202] but currently limited in laboratory or medical use. Future research holds the potential to customize local high density [99] based on the demand, which could increase sensing capability. With more detailed information like the morphological muscle structure or high-density sensors, the capability can be further expanded. 2) Multi-sensing fusion can be another potential solution for increasing capability, because utilizing more sensing modalities can potentially overcome limitations of single sensing and thus guarantee a higher capability. Currently, there are some pilot investigations towards this direction [78], [203] like fusing the sEMG and FMG from a hardware perspective and fusing the visual data with strain data from algorithm perspective [56]. Especially in the realm of sign language recognition, multi-sensing fusion is not only useful for more accurate hand gestures recognition but also can integrate the information from face expressions [53]. 3) Standardized protocols and datasets can facilitate exploring and adopting more advanced algorithms. It is evident that more data are crucial for the advanced algorithms and final performance in pattern recognition. One key problem that hinders big data acquisition is the lack of a universal standard for experimental setups and protocols. Because the sensing modalities vary, every research group builds their own hardware and collects their own data, and thus a universal standard is required. ImageNet, which not only increased classification accuracy but also boosted the research community, could provide useful insights for wearable hand gesture recognition; specifically, large volume and standard data sets are needed to push this research forward. More advanced algorithms like ResNet could then be used to expand capability towards the reproduction of every hand movement.

B. Increased Robustness

Although the first sEMG-controlled prosthesis was developed in the last century, there is still a huge gap between humankind-developed prosthesis and human hands. Robustness is still one of the main obstacles that hinders wearable hand gesture recognition devices from widespread and practical use. In this review, the word "robustness" is defined as the ability to maintain recognition accuracy against adverse factors. Since biological signals used for hand gesture recognition are highly subject-specific, changing the user or wearing locations will require the model to be re-trained, which usually takes a long time and can easily degrade the user experience. For patients with dyskinesia, deficit limb motor ability will cause higher recognition error, so additional methods may be needed to increase recognition accuracy [204].

Sensor fusion is a promising approach to generate richer signal content and increase robustness from the user side. For example, for sEMG-FMG, the advantage of sEMG is that it contains abundant information directly related to muscle activation and the advantage of FMG is that it is more stable and immune to bad skin conditions (e.g., sweat) [78]. At the same time, force signals are more sensitive to gestures with low strength (the force level of hand grip is less than 10 kg), while the myoelectricity signal is more sensitive to gestures with high strength (the force level of hand grip is more than 20 kg) [203].

Hand gesture recognition robustness is closely tied to the corresponding machine learning algorithms selected for each application. Most machine learning approaches work on a basic assumption that training data and test data are drawn from the same feature space and have the same distribution [17]. Nevertheless, this assumption does not always hold true in biological signals, especially when facing electrodes shifts or different users scenarios. To maintain a high performance, it practically requires to collect large amounts of data and train a new model for a single user, which is extremely time-consuming and labor-intensive. Transfer learning can solve this problem in two ways: 1) parameter/model-based transfer learning can be used to adjust existing model parameters or reform the structure to suit a new task, which can save the cost of training a model from scratch and improve the recognition accuracy [205]. 2) domain adaptation (feature-based transfer learning), can be used to solve the data distribution problem caused by inter-user [206], [207], inter-session [207], [208], or interface position shift [209], [210] to reduce training time and improve recognition accuracy [211], [212]. These two methods are typically used simultaneously. In the design of deep transfer neural networks, adaptation layers are included to solve the distribution problem [213], [214], and fine-tuning or other transfer methods are used to update the existing model [16], [215]–[217]. Beside sEMG, transfer learning as an universal method to improve the preference of the machine learning algorithm, can also be used in other sensing modalities like PPG [137], FMG [188] and IMU [218].

For practical use, wearable interfaces also suffer from sensor position shift, when a sensor position changes between trials, which leads to the change of signal characteristics and thus affects the accuracy of hand gesture recognition. Interface

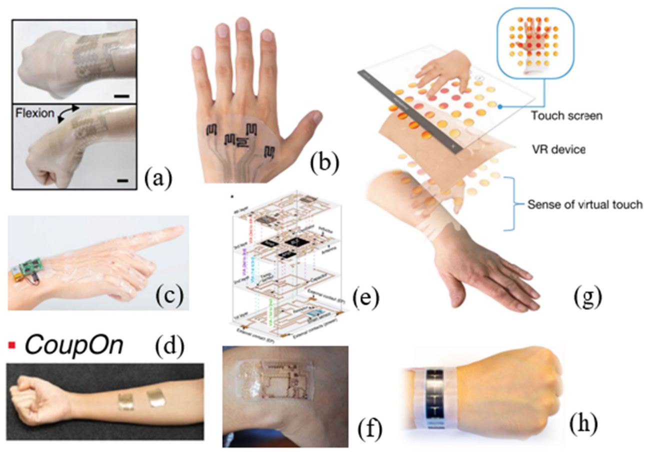

Fig. 7. Emerging studies of soft systems: (a) stretchable bioelectronics [225], (b)-(d) soft sensing e-skin/e-tattoo [65], [114], [203], (e-f) soft circuits [226], [227], (g) skin-integrated haptic device [228], (h) soft energy harvesting systems [229].

position prediction algorithms are based on two assumptions: that muscle contraction involves activation sources, and that the sEMG signal measured from an electrode is a combination of source activations [219]. Since the source parameters can be identified before the shift, the electrode location after the shift can be predicted [220]–[222]. Using high-density sensor electrodes [223] is an alternative way to solve the shift problem [224]. Conventional sEMG interfaces use four to six electrodes and after the shift happens, the recognition system loses the original and known signals and faces a different, unknown signal. By using high-density sensor electrodes and combined with approaches like the gray-level co-occurrence matrix, the recognition system can still get the original signal; only the corresponding relationship between the signal and electrodes is changed [79].

C. Soft Systems

Another vital direction for the future development of hand gesture recognition device is soft systems. Conventional wearable devices are composed of hard metal and plastic components. However, human tissue is soft, and thus the hard interface may introduce several problems. 1) Due to mismatch in device and skin hardness, the user may feel uncomfortable after long-term use. 2) The hard interface can result in insufficient contact with curved and soft human skin which may cause performance deterioration. 3) Because the Young's modulus of hard materials is not in the similar order of magnitude to the skin, the hard interface can not be stretched and moved with the skin smoothly and thus incapable of measuring certain critical characteristics like skin strain. Interestingly, the emerging advances in soft systems and prototypes have provided new avenues for more comfortable, and even imperceptible interfaces beyond the conventional form of wrist and armbands (Fig. 7). Early on Kim *et al.* [230] proposed the concept of epidermal electronics which served as a foundation for more recent cutting-edge applications of e-skin [56], [65], [114] and e-tattoos [203], [231], [232] for sensing applications. For haptic feedback, Yu *et al.* [228] introduced a skin-integrated interface which can provide localized mechanical vibrations, and Chossat *et al.* [233] proposed a soft skin-stretch device for augmented proprioceptive feedback. Advances in flexible electronics make it possible to develop soft circuits [226], [227], enabling a more user-friendly prototype. For power supply, some pilot research has even integrated energy harvesting systems based on solar energy [229] or epidermal triboelectric nanogenerators [234].

VI. Conclusion

Wearable devices for hand gesture recognition have not only played an important role in VR/AR interaction but they have also shown significant potential in rehabilitation, prosthesis control, sign language recognition, and other human-computer interaction areas. This paper presents an in-depth review of potential application areas based on hand function and the gap between human-human communication and human-machine communication. Various state-of-the-art sensing interfaces were discussed and categorized by sensing principles. In addition, irrespective of sensing principles, universal conventional machine learning algorithms and emerging deep learning methods were both reviewed. Finally, future potential directions including larger gesture sets, increased robustness and soft systems were discussed. This paper can provide readers with a detailed understanding and insights on wearable interfaces for hand gesture recognition.

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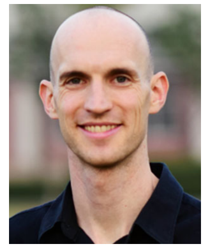

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