Human-Machine Interaction Sensing Technology Based on Hand Gesture Recognition: A Review

Lin Guo, Zongxing Lu, and Ligang Yao

***Abstract*—Human machine interaction (HMI) is an interactive way of information exchange between human and machine. By collecting the information that can be conveyed by the person to express the intention, and then transforming and processing the information, the machine can work according to the intention of the person. However, the traditional HMI including mouse, keyboard etc. usually requires a fixed operating space, which limits people's actions and cannot directly reflect people's intentions. It requires people to learn systematically how to operate skillfully, which indirectly affects work efficiency. Hand gesture, as one of the important ways for human to convey information and express intuitive intention, has the advantages of high degree of differentiation, strong flexibility and high efficiency of information transmission, which makes hand gesture recognition (HGR) as one of the research hotspots in the field of HMI. In order to enable readers to systematically and quickly understand the research status of HGR and grasp the basic problems and development direction of HGR, this article takes the sensing method used by HGR technology as the entry point, and makes a detailed elaboration and systematic summary by referring to a large number of research achievements in recent years.**

***Index Terms*—Hand gesture recognition (HGR), human machine interaction (HMI), information acquisition, sensors.**

I. Introduction

Enabling machines to work according to human intentions has been the goal of human beings since the emergence of machines. In the early days of machine development, people used buttons, joysticks, etc. to control the machine's circuit, oil, and even mechanical transmission to achieve the purpose of conveying orders to the machine. Since modern times, with the emergence of computers, the HMI environment is more and more friendly to people, people can pass information to the machine through the mouse and keyboard, and monitor their work through the display. In recent years, the size of the computer is constantly decreasing, and the working efficiency of the machine has also been significantly improved. This means that some simple input signals can control the machine to programmatically and autonomously complete complex tasks. On the basis of such technology, researchers have developed a variety of human-computer interaction technologies, such as voice control, brain-computer interaction gesture recognition, etc.

Hand gesture, as one of the important ways for human to convey information and express intuitive intention, has a variety of advantages such as strong intuition, high flexibility and rich meaning. Therefore, hand gesture recognition (HGR) is widely used and developed as a new HMI technology, and has shown great potential in many fields such as novel control mode and virtual reality, but it still faces huge challenges in the process of being put into use due to its low accuracy and lack of portability. The accuracy of HGR is closely related to the sensors, acquisition methods, and algorithms. As the hardware of HGR, sensing technology plays an important role in the process of HGR. According to different kinds of sensing technologies, HGR can be divided into different forms, which mainly include data glove, vision, and various wearable devices based on surface electromyography (sEMG) signals, ultrasonic signals, etc. This article mainly reviews the sensing technology and gesture acquisition process used in HGR.

In this article, Section II introduces various realization methods, sensing technology and acquisition methods of HGR technology; Section III compares and analyzes various sensing methods, Section IV analyzes the application direction of HGR. Section V describes the research direction and challenges of HGR technology in the future.

II. Sensing Technology for Gesture Recognition

A. Data Glove

Data glove is a common form of HGR. A data glove can be defined as a system composed of an array of sensors, electronics for data acquisition/processing and power supply, and a support for the sensors that can be worn on the user's hand [1]. In data glove, the sensors or sensor array is fixed on the special gloves by stitching or glue, which transform the motion information of hands into electrical signals according to the characteristics of different sensors and then transmit them to the data processing module. After filtering, noise reduction, and other processes, the new data are transferred to the computer and the HGR process is completed by means of machine learning. Fig. 1 shows a detailed process of HGR using most sensing methods. Obviously, the information conversion of sensors plays a key role in this process, and the different features of various sensors

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The authors are with the School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou, Fujian 350116, China (e-mail: guolin_fzu@sina.com; luzongxing@fzu.edu.cn; ylgyao@fzu.edu.cn).

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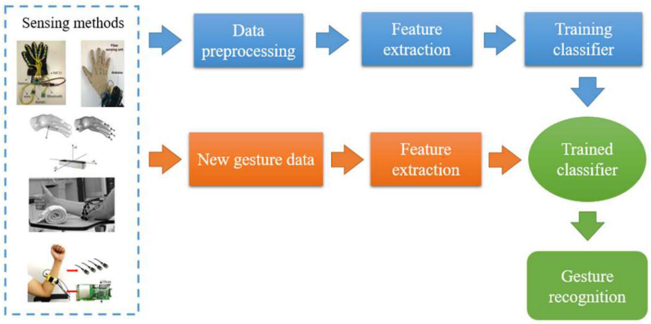
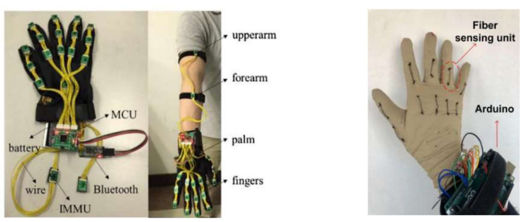


Fig. 1. Process of gesture recognition using most sensing methods.



(a) (b)

Fig. 2. Data gloves. (a) Data glove based on inertial sensor. (b) Data glove based on bend sensor.

will inevitably affect the function of data gloves. Currently, the sensors used in data gloves are mainly inertial sensors, magnetic sensors and bending sensors. Fig. 2(a) and (b) show data gloves based on inertial sensor and data gloves based on bend sensor respectively [2], [3].

Inertial sensor is a kind of sensor that detects and measures acceleration, tilt, impact, vibration, rotation, and multidegree of freedom movement. Due to its intuitive motion detection and low cost, it is widely used in data gloves. Fang [2] *et al.* designed a novel data glove for gestures capturing and recognition based on inertial and magnetic measurement units, which are made up of three-axis gyroscopes, three-axis accelerometers, and three-axis magnetometers. They obtained basic data by collecting 3-D motion information of arm, palm and finger, and used the extreme learning machine (ELM) method to trained and tested the data, then the accuracy of static recognition reached 89.59%, and dynamic gesture recognition reached 82.5%, which applied to the operation of robotic arm-hand [4]. Galka [5] *et al.* collected data on the movements of finger, wrist, and arm during sign language through an accelerometer glove, then trained and tested them with parallel hidden Markov model. The results showed that the reference accuracy [(RA), which is defined as the recognition accuracy of hand gesture in this article, namely the percentage of the ratio between the number of correctly recognized gestures and the total number of experimental gestures in the prediction experiment. However, due to the different dataset designs of different authors, the reference value of this parameter is also different. We will discuss this issue in Section III] was 99.75%. Nayan [6] *et al.* designed a data glove system containing ten angle sensors, and designed experiments to identify Indian sign language letters and American sign language letters, and obtained an average RA of 96.7% using ten-fold cross validation. In the current stage, the RA of the data gloves based on inertial sensors has reached a high level, but the sensors are relatively bulky, which affects the user experience.

In recent years, with more research on the properties of new materials, the use of bending sensors in data gloves has become widespread. Compared with inertial sensors, the bending sensors are lighter, better fitting with gloves, and have better user experience. Shen [7] *et al.* presented a soft bending sensor, and evaluated its application in data gloves. Huang [3] *et al.* manufactured a data glove by sewing the reduced graphene oxide coated fiber that is prepared in a simple method onto a textile glove, which is used to recognize hand gesture by monitoring the motion of ten finger joints from one hand, and the RA reached 98.5%. Wu [8] *et al.* presented a pair of fiber-based self-powered noncontact smart gloves with the unique function of recognizing a wide range of gestures without contact between fingertips and the palm. Compared with the traditional inertial sensing data gloves, such data gloves using fiber as sensors are more portable, which improved air permeability and comfort. Accurate measurement of thumb carpometacarpal (CMC) joint movement remains challenging due to crosstalk between the multi-sensor outputs required to measure the degrees of freedom, Dong [9] *et al.* estimated the optimal sensor locations by the least squares method, which minimized the difference between the true CMC-joint angles and the joint angle estimates. Additionally, some new sensors have been applied to HGR data gloves in recent years, Chiu [10] *et al.* proposed a self-powered gesture sensing system, which can detect the output signals of triboelectric nanogenerators arranged on the back of the hand, and successfully established a set of rules for the conversion of gestures and English letters. The features of hand joint motion used by data gloves are one of the most closely related to hand gestures. Its high accuracy in static gesture recognition is very worthy of affirmation. In the future, data gloves should be lightweight and portable.

B. Vision

HGR based on vision is a relatively mature technology, which uses cameras to capture videos of the scene containing gestures and then uses computer algorithms to identify, extract, and classify the gesture features in the images. Most of the complete hand interactive mechanisms that act as a building block for vision based HGR system are comprised of three fundamental phases: detection, tracking, and recognition [11]. In the detection stage, besides using the camera to collect the image containing the gesture, there is also an important step, that is, the segmentation of the gesture and the background. The segmentation is based on features extracted from the hand, such as skin color, shape, hand movement, etc. Sun [12] *et al.* achieved gesture segmentation and recognition by building skin color model; Indra [13] *et al.* proposed a method of recognition of Indonesian Sign Language letters based on hand-shape features; Lin[14] *et al.* proposed a gesture recognition method based on histograms of oriented gradients(HOG) features by capturing gesture trajectory information. Tracking provides users with the possibility of real-time dynamic gesture recognition. In this stage, the computer needs to continuously track the corresponding relationship between

Fig. 3. HGR based on vision. (a) Kinect. (b) Leap Motion.

the features of each frame of the hand through the algorithm. Finally, the computer realizes the recognition and classification of gestures through machine learning algorithms such as support vector machine (SVM) and hidden Markov model (HMM). Pramod [15] *et al.* reviewed a large number of methods based on visual gesture recognition and the comparison of algorithms.

When it comes to sensing devices based on visual gesture recognition, the average RGB camera in the market is generally up to the task. The higher the quality of the camera and the higher the number of pixels, the greater the accuracy of gesture recognition and the greater the load on the computer. Nowadays, with the development and application of structured light technology and depth sensor, 3-D visual gesture recognition technology and stereo vision gesture recognition technology have been widely applied and rapidly commercialized. For example, disparity map-based centroid movement and changing of its intensity are used as the feature based on stereoscopic vision [16], and used conditional random field (CRF) as the classifier to recognize gestures. Their experiment verified that the average recognition rate reached 88%.

At present, the mature typical commercial products include Kinect, Leap Motion etc. as shown in Fig. 3(a) and (b) [17], [18]. By using this kind of equipment with more complete functions and higher reliability, many scholars and related professionals have developed effective methods and algorithms for HGR [19]. A recognition algorithm based on Kinect sensor is proposed by Wu *et al.* [20], and compared it with the traditional method to verify that its RA has been significantly improved. Murata [17] *et al.* tested the Kinect sensor's ability to recognize numbers and alphanumeric characters written in the air, and the results showed that the average rate of the number and alphanumeric characters was 95.0% and 98.9%, respectively. Kinect sensor is also used to recognize Arabic numerals and English letters written in the air based on the trajectory characteristics of fingertips, and obtained a high accuracy [21]. Leap Motion with the model based on constant radial basis function (RBF) neural networks was verified by experiments [18]. Almarzuqi [22] *et al.* used Leap Motion depth sensor for gestures recognition to improve the accuracy of intelligent system when interacting with robots.

The hardware of visual gesture recognition is relatively simple, but it requires higher computational costs due to the necessity of processing 2-D or even 3-D image data. Furthermore, the gesture recognition based on the principle of optics is limited by the focal length and covering range of the camera, so it is easy to have blind areas of vision and blocking of light, which will affect the RA and the user's activity range. Ahmad

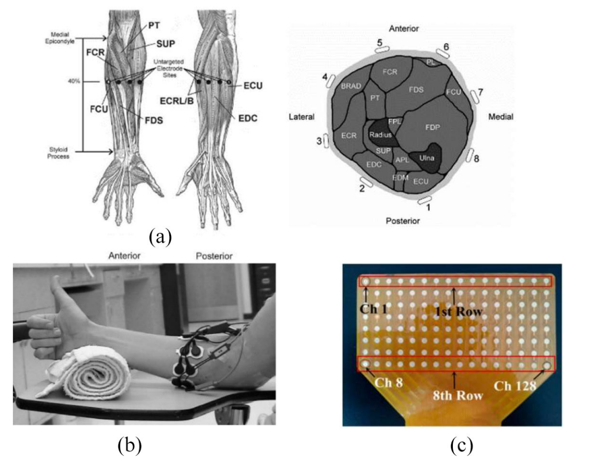


Fig. 4. Surface electromyography. (a) Relationship between gesture and forearm muscle. (b) Wet electrodes. (c) Dry electrodes.

et al. systematically summarized and discussed the problems and challenges of visual gesture recognition from three aspects: system (challenges of response time and cost factor), environment (challenges of background, illumination, invariance, and ethnic groups) and gesture (challenges of translation, scaling, rotation, segmentation, feature selection, dynamic gesture, and size of dataset) [23].

C. Surface Electromyography

Human hand movement is driven by the contraction and stretching of forearm muscles as shown in Fig. 4(a) [24]. When describing the anatomical position of forearm muscles, flexor carpi radialis and flexor carpi ulnaris muscle play a major role in wrist joint movement [25], which are responsible for finger bending and extension. The obvious correlation between forearm muscle and hand movement provides the possibility for HGR based on forearm muscle characteristics. The acquisition methods of forearm muscle movement information mainly include sEMG, ultrasound (US), forearm shape detection, and mechanomyography (MMG).

sEMG signals are collected by the contact between electrodes and the skin of the body. The resulting EMG signal is the summation of the action potentials discharged by the active muscle fibers in the proximity of the recording electrodes [26]. These electrodes are generally divided into wet electrodes and dry electrodes, as shown in Fig. 4(b) and (c) [24], [27]. Wet electrodes have lower skin contact impedance to reduce the influence of external interference sources to the electromyographic signal electrode and improves the signal-to-noise ratio. The wet electrodes can be freely pasted to any position on the skin surface in the arrangement without additional fixation, but due to the existence of the gel, the occupied area is larger, so the wet electrodes cannot be used for more channels signal acquisition. In contrast, the dry electrodes are easy to be integrated into the sleeve and other devices for multichannel array collection due to its small size and large layout space without the presence of gel. However, due to its lack of viscosity, additional fixation device is needed to make it stick to the skin surface.

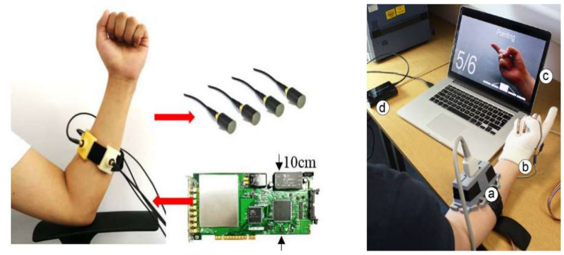
As other sensing methods, the HGR technology based on sEMG also uses machine learning method for classification, but the algorithms contain fewer dimensions of features and are easier than the visual method. In recent years, many scholars have proved the feasibility of sEMG method in experiments and system design. Hu [28] *et al.* designed a human-machine coordinated control system that can recognize 8 gestures of subjects in real time by wearing an array of sEMG sensors and control a six-degree-of-freedom dexterous fake hand for synchronous movements. Ketyko [29] *et al.* proposed a domain adaptation method based on deep learning, and verified the superiority of this method. A novel method is proposed for pattern recognition and compared the classification effect with different algorithms for able-bodied and amputees [30]. Fang [31] *et al.* proposed a clustering-feedback strategy to improve the accuracy of EMG online pattern recognition. Different from other sensing methods, the method based on muscle activity characteristics can also identify and estimate grip force. There is a strong correlation between muscle force and sEMG signals [32]. Xu [27] *et al.* verified the feasibility of three different types of neural network algorithms for force estimation based on sEMG through experiments. Wang [33] *et al.* proposed a wavelet scale selection technology based on nonlinear correlation to select effective the wavelet scales from sEMG signals to estimate grip force. Fang [34] *et al.* proposed an attribute-driven granular model under a machine learning scheme and it was fulfilled for EMG-based pinch-type classification and the fingertip force grand prediction. Of course, sEMG signals also have some shortcoming, mainly reflected in weak signals and crosstalk, as well as the impact of inevitable movement of dry electrodes in the process of wearing. The denoising of sEMG signal is a very important topic. Baspinar [35] *et al.* studied three different denoising methods of sEMG. Wu [36] *et al.* reviewed the denoising methods of sEMG signals. Aiming at the problem of robust motion recognition, Minjae [37] *et al*. proposed an sEMG interface rotation compensation method. It is worth mentioning that the amputee's motion intention can still generate relevant sEMG signals on the body, so sEMG signals have some unique advantages in assisting the disabled [38], [39]. Fang[40] *et al.* reviewed a lot of research on interacting with prosthetics based on the sensing techniques including EMG, SMG, MMG, EEG, ECoG, ENG, etc.

D. Ultrasound

As mentioned in the previous sections, wearable HGR system based on the sEMG have made some achievements in the experiments and practical applications, but the sEMG still have some defects such as weak signal and poor penetration, which affecting the user experience. In recent years, scholars have turned to US that has greater penetrating power.

Sound waves are mechanical waves and travel by repeatedly compressing and expanding the medium. The complex ratio of the sound pressure p to the particle velocity v at a certain point in the medium is called the acoustic impedance, that is

$$Z_s = \frac{p}{v}\,. \tag{1}$$



(a) (b)

Fig. 5. US-based HGR. (a) Acquisition methods of A-mode US. (b) Acquisition methods of B-mode US.

In general, the plane harmonic acoustic impedance of one-dimensional forward propagation can be expressed in the following form

$$Z_s = \rho c \tag{2}$$

where, ρ is the density of medium, and c is the speed of sound. The acoustic impedance of plane sound wave is a real number, and only depends on the nature of the medium itself and the speed of sound, that is also known as the acoustic characteristic impedance of the medium. When sound waves pass from one medium to another with different impedance characteristics, echo is reflected at the boundary. The proportion of echo is proportional to the impedance mismatch between the two media. If we send a series of ultrasonic pulses to the forearm muscle, we can get the muscle movement and shape information by detecting and analyzing the echo signal.

The acquisition methods of US are divided into A-mode and B-mode. Fig. 5 shows the gesture recognition equipment of A-mode and B-mode US, respectively [41], [25]. Yang [41] *et al.* designed a gesture recognition method based on multi A-mode US, with an offline accuracy of 98.87% and an online accuracy of 95.4%. Hettiarachchi [42] *et al.* introduced a new wearable ultrasonic radial muscle activity detection system and obtained good gesture RA through experiments. Sun [43] *et al.* compared the dual-frequency transducer of A-mode ultrasonic probe with the single-frequency transducer, and the results proved that the dual-frequency transducer has better performance. Yan *et al.* [44] designed a new lightweight A-mode ultrasonic probe and verified its classification effect of gesture recognition. B-mode ultrasonic, namely luminance (brightness) model to 2-D imaging of echo signal, reflects more information and covers a wider range of the muscles. However, the US imaging often requires more complicated algorithm and visual identification of the relevant methods for feature extraction, its processing and recognition algorithms have certain similarities with visual way. Gesture recognition method is proposed based on B-mode US without repeated training, and the RA reached 94% [45], [46]. Akhlaghi [47] *et al.* used US images to identify six participants in 15 different gestures, the results showed an offline RA of 91% and an online real-time RA of 92%. Compared with sEMG signals, US signals can penetrate deeper muscles and ensure higher accuracy. Youjia Huang [48] *et al.* compared the recognition methods based on B-mode US and sEMG signals, then found that the ultrasonic method (95.88%) was higher than sEMG method (90.14%). At the same time, the US method can get rid of more wires in gesture recognition wearable devices, but the current B-mode US device probe is still relatively bulky, and the US gel needs to be applied to couple between the probe and skin, which affect the user's experience, and these gels add to the cost and sometimes affect the performance of the recognition. McIntosh [25] *et al.* explored the placement of US probes, which has certain guiding significance for the design of wearable devices based on US, and many scholars are also studying how to reduce the cost of ultrasonic gels and improve their performance [49], [50].

E. Other Methods

HGR is closely related to the change of forearm muscle morphology, which will inevitably cause the change of forearm transverse section shape. It is a novel way to extract gesture information by detecting such shape changes with piezoelectric sensors. Zhang [51] *et al.* used four pressure sensors to realize gesture recognition. Booth [52] *et al.* recognized the motion of five-finger tapping by placing six piezoelectric sensors inside the wrist band to recognize the changes in wrist shape, and its RA reached 97%. In addition to piezoelectric sensors, optical sensors can also be used to extract the changing features of the arm shape for gesture recognition [53]. Although these detection methods can achieve high accuracy in the recognition of individual gestures, they are still unable to collect the movement information of deep muscles and have great limitations in the recognition of flexible gestures. In some studies, muscle movement information of forearm was collected by means of MMG, this method collects signals by recording the vibration signals produced by the process of muscle contraction. The same as ultrasonic method to detect muscle acoustic signal for HRG, this kind of method is to detect the spontaneous acoustic signal of muscle, its signal strength is far less strong than that of ultrasonic detection, and it is easy to be interfered. Wilson [54] *et al.* use this method for recognition of 12 hand gestures, the offline RA is 89%, and the real-time RA is 68%. In recent years, some scholars focused HGR on the WiFi signals and radar signals. Tian [55] *et al.* introduced a method through transmitting and receiving weak WiFi signals for gesture recognition. System with leverages changing in WiFi signal strength is presented to sense in-air hand gestures around the user's mobile device [56]. Some novel continuous HGR system is proposed based on singular radar and dual-channel doppler radar sensors [57], [58]. Ryu [59] *et al.* introduced a frequency modulated continuous wave radar system for HGR. These methods as new types of HGR can get rid of the shackles of wearable equipment. In the future, they may become the new application method of HGR equipment.

F. Hybrid Methods

Different sensors can detect different and limited gesture-related features. Just as the inertial sensor can collect the motion features of the hand, the visual or optical method can collect the shape and depth features of the gesture, as well as the motion features of the forearm muscles by sEMG and US. The limitation of each method is that it limits the improvement of HGR performance. In recent years, the development of HGR system and technology by integrating a variety of sensing technologies and collecting a variety of features has gradually entered people's vision. As a result, many molding products have been derived and even commercialized. Along with the aforementioned Kinect and Leap Motion, which integrate camera, depth sensor, voice recognition, and other functions, there are also Myo bracelet and gForce bracelet, which integrate sEMG signal sensors and inertia sensors. Xia [60] *et al.* designed a device that integrated sEMG method and A-mode US method for acquisition. Experimental results show that the RA of the system is 20.6% and 4.85% higher than single sEMG method and A-mode US method. Zhang [61] *et al.* designed a new system, which trained and tested the acquired signals of inertial measurement unit, EMG, pressure data of finger and palm, and established an effective gesture classification model based on long short-term memory algorithm of deep learning technique. Guo [62] *et al.* used data gloves and Kinect to obtain the data of changes in the angle of finger joints and the data of centroid motion of hand for gesture recognition. Accelerometer signal and sEMG signal are used to HGR, and the results showed that the RA of this method improved to a certain extent [63]. Molchanov [64] *et al.* proposed a new system that uses short-range radar, color camera, and depth camera to recognize the gestures of drivers in cars. Skaria [65] *et al.* used miniature radar sensors to pick up gestures and classified them, with an accuracy of more than 95%. Wilson [66] *et al.* used inertial sensors and MMG for HGR and control of prosthetic hand.

III. Comparison and Analysis

Table I shows the different methods used in several mainstream sensing methods and the RA of recognition in relevant literatures. In the table, the definition of reference accuracy varies according to the calculation methods used in different articles, and the specific content of the literature shall prevail. Obviously, there are certain differences in the sensing methods, algorithms and processing processes used by the authors, so that the final results are also quite different. It is worth mentioning that the size of the dataset, the type of gestures and some verification methods used by the authors in their gesture recognition experiment are listed in Table I. In general, we believe that the higher the RA, the better the performance of the method. However, the reference value of this parameter varies according to different datasets and experimental designs. The more kinds of gestures, the more difficult the classification; the larger the sample size, the more convincing the RA. Through comparison and analysis, these methods and processes will have great reference value for the future research work. We also mention several different gesture types in Table I, which by default refer to static gesture recognition if we do not specify them separately. We summarize the advantages and inherent defects of various sensing methods in applications and show them in Table II. Through comparison, it can be found that the HGR system based on data gloves has higher robustness, the overall system is stable, the sensor

TABLE I
COMPARISON OF DIFFERENT METHODS USED IN HGR

Authors	Sensing Method	Algorithm	Dataset(gestures*persons)	Reference Accuracy
Paweł Pławiak et al.[67]	Data glove	SVM+GA	22*10, 10-fold cross validation	98.24%
Nayan M. Kakoty et al.[6]	Data glove	SVM	44*4, 10-fold cross validation	96.7%
Xin'an Huang et al.[3]	Data glove	NN (static gesture) DTW (dynamic gesture)	10*4(static gesture) 9*4(dynamic gesture) 2 persons for training, 2 persons for testing	98.5% (static gesture) 98.3% (dynamic gesture)
Bin Fang et al.[2]	Data glove	ELM-kernel (static gesture) ELM-DTW (dynamic gesture)	10*2(static gesture) 16*2(dynamic gesture)	89.59% (static gesture) 82.5% (dynamic gesture)
Wei Zeng et al.[18]	Vision (Leap Motion)	RBF	10*10(writing in the air), 10-fold cross validation	95.1%
Fenglin Liu et al.[21]	Vision (Kinect)	RBF	10*10(writing in the air), 10-fold cross validation	97.25%
Mohidul Alam Laskar et al.[16]	Vision	CRF	10 gestures*15 video pairs	88%
Peijun Bao et al.[68]	Vision	deep CNN	7*40, 25 persons for training, 5 persons for validation, 10 persons for testing	97.1% (simple backgrounds) 85.3% (complex backgrounds)
Abhik Singla et al.[69]	Vision (Leap Motion)	HMM	36*10(writing in the air), 5-fold cross validation	92.87%
John Jairo Villarejo Mayor et al.[30]	sEMG	SVM	13*10(able-bodied) +10(amputees), 5-fold cross validation	99.2%(able-bodied) 98.94%(amputees)
HU Xu-hui et al.[28]	sEMG	NN	8*1,80% data for training, 20% data for testing	97%
Zhen Ding et al.[70]	sEMG	CNN	17*40	78.86%
Xingchen Yang et al.[41]	Ultrasound (A mode)	LDA	11*8, 5-fold cross validation	98.83%±0.79% (offline) 95.4%±8.7% (real time)
Jipeng Yan et al.[44]	Ultrasound (A mode)	LDA	11*5	97.64%±1.83%
Youjia Huang et al.[48]	Ultrasound (B mode)	LDA	14*8, 2-fold cross validation	95.88%
WEI XIA et al.[46]	Ultrasound (B mode)	LDA, SVM, KNN, RBF SVM	29*15,	About 90%
Riley Booth et al.[52]	Piezoelectric sensors	SVM	5*10	97%
Samuel Wilson et al.[54]	MMG	A template-based classification algorithm	12 gestures for offline and 7gestures for real time, 5 healthy participants and 1 transradial amputee	80% (offline) 68% (real time)
ZENGSHAN TIAN et al.[55]	WiFi	SVM	9*10	95%
Guo Xiaopei et al.[62]	Kinect & data glove	improved WPCCs	40*3	97.7%
Wei Xia et al.[60]	sEMG & ultrasoud	SVM	20*8	89.20%±3.24%

Algorithms instructions: support vector machine (SVM), genetic algorithm (GA), neural network (NN), dynamic time warping (DTW), extreme learning machine (ELM), radial basis function (RBF), conditional random field (CRF), convolutional neural network (CNN), hidden Markov model (HMM), K-nearest neighbors (KNN), radial basis function based support vector machine (RBF SVM), weight-based Pearson correlation coefficient (WPCC).

TABLE II
ANALYSIS OF DIFFERENT METHODS USED IN HGR

Sensing Method	Wearable	Recognizable gesture type	Advantage	Defect
Data glove	Yes	static & dynamic gesture	Robust, low cost, no arear limit	Low comfort, unwieldy
Vision	No	static & dynamic gesture, writing in the air	Mature technology and products, unconstrained, comfortable, free hand	Complex algorithm, easy obscured, Influenced by background
sEMG	Yes	static & dynamic gesture, gestures of amputees	Portable, low cost, free hand	Weak signal, crosstalk, affected by the change of wearing position
Ultrasound	Yes	static & dynamic gesture, gestures of amputees	High accuracy, free hand, robust	Heavy equipment, need ultrasonic gel, affected by the change of wearing position

has low cost and the accuracy is higher, but it is inconvenient to wear, which affects the application and user's experience. Compared with other methods, visual gesture recognition gets rid of the hands and arms bondage, but the recognition area is also limited to the space that captured by the camera. From the perspective of technology, visual recognition is relatively mature and there are many researches and achievements. sEMG has an advantage in cost, but its accuracy is often affected by its weak signal. Although the method of replacing the forearm muscle recognition with ultrasonic signals can improve the accuracy, it is difficult to achieve commercial application due to some problems, such as the high cost of equipment and the inconvenience of wearing. From the recognizable gesture type, we can see that visual mode can recognize gesture in air writing, which is more suitable for dynamic information transmission. SEMG signals and US signals are particularly useful in the field of medical rehabilitation because they can be worn on the forearm to recognize the gestures of amputees.

In fact, from the content described in Table II and existing commercial products, we can find that the sensing systems that can be truly popularized and successfully applied in daily life are those that are more portable to use, such as Kinect in visual mode and Myo armband based on sEMG, which can make the hands get rid of the shackles and be more favorable to people. Specific applications need scholars and researchers to choose according to the actual application scenarios.

IV. Applications

Human–computer interaction system consisting of a variety of sensing technologies has great development and application potential. This section summarizes the applications of HGR technology in the following five directions.

A. Simplify or Replace Traditional Control Methods

More intuitive and convenient methods of HMI such as HGR will gradually replace traditional control methods such as switches and buttons. This is an obvious trend, just as buttons and switches replaced manual operation methods. In fact, HGR shows great potential in various scenarios of daily life, and performs better than traditional control methods. N.Lalithamani [71] applied single web camera-based gesture recognition technology to controlling the mouse cursor, the clicking actions, and few shortcuts for opening specific applications. Rajesh [72] *et al.* expounded the application effect of HGR in traditional joysticks controlled wheelchair, and showed that the application in wheelchair was a better choice based on experimental results and users feedback. Shalahudin [73] *et al.* developed a controller prototype to facilitate family life by controlling lamps and other home devices through HGR. At the same time, because of the intuition and convenience of it, HGR has shown a good effect on the substitution of traditional joystick, button, etc. in 3-D motion mode, which is mainly reflected in the control of mobile machinery, mechanical prosthetic hand, etc. Luo [74] *et al.* realized the control of a Mecanum-wheeled mobile robot through the recognition of two-hand gesture, and verified the system could timely, accurately and stably complete the tasks of directional movement, grasping and clearing obstacles in the control experiment of mobile robots. It has been proven that HMI is a better alternative to the traditional control method.

B. Human–Machine Cooperation

Many applications of HGR to replace traditional controls have been mentioned. In fact, HGR also has development potential in controlling industrial robots. Nuzzi [75] *et al.* built a gesture recognition model for collaborative robots. Du [76] *et al.* propose a natural human–robot interface using an adaptive tracking method, which get rid of the limitation of accuracy and operating space of traditional HMI, and improves the user experience and reduces the complexity of operation. Neto [77] *et al.* proposed a method to program industrial robots by using a hand-held accelerometer-based input device to recognize gestures and voice, which can better replace the traditional process of industrial robot teaching and programming, improve work efficiency and save time. At present, many studies have shown that HGR can realize the control of robots, but most of the control is one-way control of robots by humans, that is, humans make simple associated actions to control the actions of robots. We believe that with the in-depth study of sensing technology and algorithms, robots will be able to recognize and analyze human hand movements based on the information obtained from sensors when humans are engaged in some complex manual activities, and autonomously make coordinated actions to assist human to complete the work. These are not utopian ideas, but rather a development direction that can be fully realized in the light of existing technical conditions. The application of HGR to human-computer collaboration will help humans to complete work more efficiently, after all, some work robots are more expensive to complete, while others are more suitable for humans to complete manually. Whether this kind of man-machine collaboration can be realized depends on the optimization and development of sensing technology and algorithm in the future.

C. Sign Language Translation

Hand gesture as one of the most important body languages of human beings also plays an important role in the interpersonal communication. The standard sign language can be translated by HGR technology, which overcomes the communication barrier between deaf-mutes and ordinary people who do not know sign language, and realizes the auxiliary communication to the people who are lack of language expression. Zhang [78] *et al.* proposed a sign language recognition system that recognizes gestures by extracting key frames of videos. Wei [79] *et al.* proposed a component-based vocabulary extensible sign language recognition framework using data from surface electromyographic sensors, accelerometers, and gyroscopes, implemented recognition experiments under different size of training sets on a target gesture set consisting of 110 frequently used Chinese Sign Language sign words and achieved high RA. A 3-D recognition model is proposed for Indian Sign Language recognition [80], and verified that the motionlet based adaptive kernel matching algorithm on 500 class 3-D sign language data gives better RA compared to state of the art action recognition models. Neiva [81] *et al.* reviewed the work of scholars on sign language recognition technology in detail, especially in mobile situations, and summarized the research direction of sign language recognition technology.

D. Interactive Entertainment and Virtual Reality (VR)

HGR technology also plays a key role in interactive entertainment and virtual reality. In the process of interactive entertainment, people mainly use hand gestures as input signals to transmit to computers, televisions, and other entertainment devices to get visual and auditory feedback to complete the entertainment process. For example, one of the main functions of Microsoft's Kinect, is the ability to recognize body movements to provide input signal for many supporting video games. In the future, with the improvement of signal transmission speed and sensor accuracy, HGR will be further applied in the field of virtual reality, and hand movements will also be able to be reproduced in VR. HGR based on Leap Motion is applied to rehabilitation training on subacute stroke based on virtual reality and verified its effect through experiments [82].

E. Correction of Standard Actions

Because the HGR technology can make hand movements be quantified, it had a surprised effect that people can correct and teach some activities that need to be regulated based on the quantified gesture data. For example, Sufen [83] *et al.* used inertial data glove and infrared detection rod to collect and identify the gestures and piano keys of people when they played the piano, which realized real-time correction of piano playing gestures. In the future, this technique could be used to train many professional skills based on hand movements. The quantified gesture data will provide a standardized parameter for gesture movement, through which people can learn more professional gestures and correct their own movements.

V. Future Works

HGR technology as a novel technology has been gradually accepted by the public and has caught the attention of more and more enterprises and scientific research workers. At present, many enterprises have begun to develop equipment for HGR. There are many research institutions designing some HGR systems, and have also made a higher classification accuracy. As the basis of HGR, the sensor technology will develop significantly in the future. This article roughly divides its future development into three major directions.

A. Integration of Various Sensors

Section II mentioned that there are many research results integrated of various sensing methods. With the continuous progress of future researches, more and more combination methods of sensors will be verified by experiments to achieve a better RA.

B. Look for New Features

Feature extraction is a key process in pattern recognition, and the richness of features also affects the accuracy significantly. Different sensors can extract different gesture signal, and more new features associated with gestures can be found by searching for new sensors, so as to develop an HGR system with better performance. In general, the higher the correlation between the selected features and gestures, the easier the classification and the better the modeling effect will be. Therefore, it is one of the future work contents to explore the features with higher degree of correlation. However, the type of feature often affects the generalization ability of the HGR system. Before designing the HGR system, we should first recognize whether the system is for the entire human group (such as the shape of the hand and the bending of the joint) or for the use of individuals (such as the related features of the forearm muscles). These features are different in the selection of different application scenarios, and how to use these features determined by us according to different work requirements is also an important content of future work.

C. Develop New Algorithms

Most data from the sensors are needed for the processing of machine learning algorithms to classify gestures. From many research results, we found that the matching of different algorithms and different sensing methods would lead to different results. Through the comparison and analysis with experiments, the combination of algorithms and sensors with higher relative matching degree can be developed in the future.

There are still many challenges in HGR technology. RA is the key parameter of user's experience, how to break through the bottleneck of RA is to be solved urgently. In addition, how to improve the wearing portability of the system is also an important issue. We need to constantly explore new ways, such as switching from wired connections to Bluetooth connections or reducing the weight of our wearables through craftsmanship.

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