Multimodal Human Hand Motion Sensing and Analysis - A Review

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***Abstract*—Human hand motion analysis is an essential research topic in recent applications, especially for dexterous robot hand manipulation learning from human hand skills. It provides important information about the gestures, tactile, speed and contact force, captured via multiple sensing technologies. This paper introduces a comprehensive survey of current hand motion sensing technologies and analysis approaches in recent emerging applications. Firstly, the nature of human hand motions is discussed in terms of simple motions, such as grasps and gestures, and complex motions, *e.g.* in-hand manipulations and re-grasps; secondly, different techniques for hand motion sensing, including contact-based and non-contact-based approaches, are discussed with comparisons with their pros and cons; then, the state-of-the-art analysis methods are introduced, with a particular focus on the multimodal hand motion sensing and analysis; finally, cutting-edge applications of hand motion analysis are reviewed, with further discussion on facing challenges and new future directions.**

***Index Terms*—multimodal sensing; human hand manipulation; tactile sensors; vision-based sensors; hand motion analysis**

I. Introduction

NOWADAYS, robots are widely applied to complex surroundings: aerospace, field operations, and social applications. These new applications require robots to perform complicated dexterous in-hand manipulation tasks instead of humans. The robotic hand control is an integrated product in multi-disciplines, which cover pattern recognition, bionics, tactile sensing and many other disciplines [1]. However, it's not easy to integrate and implement the corresponding techniques to achieve human-like manipulation. The development of a sophisticated multi-fingered robot hand is still at an early stage, because of the lack of appropriate multi-fingered control system structure, the immature synchronous cooperation between sensor-motor systems, biomimetic materials issues, *etc*. In order to meet the sound reliability and flexibility of bionic multi-fingered robotic hands, as well as the real-time performance, it is crucial to achieve these targets through human hand motion (HHM) analysis, HHM capture, HHM recognition and HHM skill transfer [2].

Based on acquired skills and past experience, human can perform various operational tasks easily. However, there are some 'engineering challenges' considerations to take into account when manipulating a specific object by robotic hands, namely, contact point layout problem, pre-grasp pattern optimization problem, grasping force matching issues, and coordinated manipulation strategy selection [3], [4]. In the past decades, robotics researchers have devoted their attention to the study of human hand manipulative skills. Kang *et al.* segmented the human hand motion based grasping task sequences into three basic identifiable phases: pregrasp phase, static grasp phase, and manipulation phase. Then, a task division algorithm was used to demonstrate the viability of these motion transformations [5]. It is recognized that the state-of-the-art HHM analysis theory has capabilities of establishing hand manipulative skill model, however, realizing some advanced functionalities of a robotic hand, that is, manipulative dexterity, grasp robustness, and human-like operability, is still a challenge in a complex interactive environment [6].

While performing different operating tasks, human can select appropriate grasping strategies and applied forces according to the characteristics of objects (shape, size, weight, *etc.*). Realizing hand dexterous manipulation is a complex process, involving multimodal sensing and fine motor control. Only extracting skeleton postures from the human hand is not enough, and more characteristics of HHMs, such as finger force, tactile, speed, *etc*, are also very important [7]. With the rapid development of electromechanical and sensing techniques, the multimodal sensing system is suitable for a robot hand to efficiently acquire shape, position and orientation of an object, which could be operated in a smart way. Generally, the hand motion sensing systems can be mainly divided into: data glove based capturing, attached force based capturing, surface electromyography (SEMG) based capturing, optical markers based capturing and vision based capturing. A data glove is a particular glove that has sensors, typically magnetic or in optic fibre to measure the finger bending. Attached force sensors construct the sensing system through the changes of capacitance, resistance or electrical charge. SEMG signals can be used to obtain the information of contracted muscles, and then to generate control commands for the prostheses control. Optical markers are used to simplify the capture procedure and describe the hand motion configuration in a low-dimensional space. Vision based motion capturing is widely applied to capture images of hand motions by cameras. Compared with other technologies, the vision sensor can work in a natural and non-contact manner [8]. In recent years, the available vision sensors, such as the Kinect and leap motion controller, have been successfully used to the sign language and hand gesture recognition. Increasing efforts have been made in acquiring the characteristic information, however, most of the current research has focused on a range of limited behaviours or in

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limited scenarios based on a single type of sensing system [9]–[12]. It remains to be a tough issue for a complex hand motions, like in-hand manipulation. For example, Given a data glove based human hand manipulative information, a robot hand is required, inspired by human hand biological capabilities, to manipulate the same size and shape of egg and briquette. Due to the lack of important finger force control and spatial location information, the manipulation will probably fail. Hence, the researchers now face is how to obtain the multimodal features of hand manipulations through perceptual fusion techniques.

A comprehensive review of current state of the multimodal sensing technologies and motion analysis approaches on human hand motion recognition and its emerging applications is presented as follows. The natural classifications of the hand motions are reviewed and discussed, followed by a detailed description of HHMs from two aspects in Section II. Section III overviews sensing techniques for HHMs and presents a thorough taxonomy. An overview of hand motion analysis methods is discussed in Section IV. The multimodal hand motion sensing techniques are presented and discussed in Section V. Section VI shows various applications of HHM analysis in different environments. Section VII gives a detailed summary and discussion, as well as future research directions.

II. Human Hand Motions

The human hand is one of the most complex and dexterous motor systems in the human body for communication and interaction [13]. HHM analysis has become an important bionic research topic for scientists and engineers to design human-like robots and prosthetic hands for different tasks by learning and modelling human hand skills. Elliott *et al.* first proposed a comprehensive classification framework to describe four broad classes of HHMs [14]. Exner developed five types of HHMs on the basis of work of Elliott and Connolly [15]. Pont *et al.* presented an improved classification system and further described six types of HHMs [16]. More recently, Fougner *et al.* proposed a multimodal approach using EMG and accelerometers to realise eight classes of HHMs [17]. Bullock *et al.* designed a hand motion-centric based classification scheme to create a descriptive framework [18], which was used to effectively depict HHMs during manipulation in complex and changing environments, and other existing classification methods were also integrated into the framework to describe the specific manipulation tasks. In this paper, a new classification strategy is proposed, namely, simple hand motions, including various grasps and postures, and time-varying complex hand motions, for instance, the dynamic gestures and complex rotations.

A. Simple hand motions

Simple hand motions are very common in the real life, including grasp, lift, hold, put, rotation, and gesture. Most hands-on work can be done with simple hand motions: picking up a phone, grasping a bottle, putting down a cup, *etc*. These motions are completed through one or several types of sub-actions and finger primitives. Mitra *et al.* presented a detailed summary on gesture recognition [19]. They categorised five human gestures to describe the HHMs: gesticulation, sign language, language-like gestures, pantomimes and emblems. Although this classification presents a summary of hand motions, there is no specific description of in-hand manipulation.

Different movements involve different numbers of fingers. Fingertips are used to maintain the grasp stability by applying proper normal force and tangential force [20]. Five types of simple motions are proposed based on the multi-fingered configuration as shown in TABLE I. It is easy to acquire some characteristics of the hand and segment the motions into some sub-actions, but they are limited in complex or advanced tasks.

TABLE I: Classification of simple hand motions

Classification	Examples
Static gestures	Victory sign Pointing a finger projection Thumb up
Touching	Pressing a button Pushing a closed door Sliding a pen on the table Flipping a light switch
Stable grasps without external forces	Holding a phone Grasping a coin on the palm Writing with a pencil Cutting a paper with a scissor
Simple shifts	Lifting a water glass Pushing a key into a keyhole Taking a book from a shelf Putting a cover on
Rotating an object in-hand	Screwing/unscrewing jar lids Rolling pingpang among fingertips Turning doorknob Spinning a small top

B. Complex hand motions

Complex motions generally include three main features: (1) multi-fingered movements with or without the palm, (2) wrist movements cooperating closely with in-hand manipulation, (3) changes in the hand's location and posture. Ju *et al.* proposed a nonlinear feature extraction based classification approach to identify different hand manipulations [21]. Lu *et al.* identified the features of several in-hand manipulations, and recognized these hand manipulation signals based on BP neural network and support vector machine classifiers [22]. Complex HHMs show more flexible and dexterous human in-hand operations, so it is more difficult to describe the process for multi-fingered manipulation [23]. The classification of complex motions with applications in manipulation tasks is presented in TABLE II.

Based on temporal relationships, the dynamic gestures change continuously with respect to the hand's location, and the related messages can be obtained in the temporal sequence through hand trajectories, orientations, the fingers' shapes and flex angles. In-hand manipulation can be decomposed into a sequence of sub-motions, and it is much more complex than simple grasp motions and associated with the most complex human motor skills. It's the ability to change the position or adjust an object within one hand. Regarding the examples of simple shift in TABLE 1, all the participating fingers with or without the palm move with the object as one

TABLE II: Classification of complex hand motions

Classification	Examples
Dynamic hand movements	Sign language movements Finger gymnastic
Complex shifts	Fanning the playing cards in the hand Adjust fruit while eating
Complex rotations	Turning over coins in-hand Spinning a pencil like a ”helicopter” in the fingertips
Complex two-hand cooperations	Carrying a box with two-hand Telerobotic remote surgical service

unit. However, complex shifts combine shifts with sequential pattern movements of an object, and the participating fingers are independent of each other to form a different action schema. In addition, discontinuous movements occur when repositioning some fingers on the object, while the others move together. For a complex rotation, an object will be rotated around one or more axes. The participating fingers and the thumb are required to execute isolated and independent finger movements to complete a rotation. In addition to the above complex motions, two-hand cooperation is another important type of HHMs. This kind of interaction requires precise physical models so as to allow interaction among users, who are manipulating objects at the same time.

To facilitate a good human robot interaction, it is necessary to have a precise physical model for HHM analysis. Advanced manipulations have been widely applied to telerobotics [24] and surgical applications [25]. However, most of the current research is focusing on the dual-arm operation, and the dual dexterous hand operation has not been properly addressed.

III. Sensing Technologies for Human Hand Motions

Humans develop robust control strategies to achieve the complexity and dexterity of HHMs through extracting regularities in sensorimotor interaction with the external environment. Fig. 1 shows a detailed categorization of current sensing technologies. The contact-based sensors acquire sensing information, attached on the human hand or other parts of the body. Depending on tasks, sensory information obtained from various contact-based sensors can be applied to track the contact locations, reconstruct, recognize the physical characteristics of the objects, and measure the tactile parameters. In contrast to various contact-based sensors, vision-based sensing systems can acquire the information without physical touch. In the following sections, this paper will explore in more depth the functions and characteristics of each sensing device.

A. Contact-based sensing technologies

1) Hand data glove: Hand data glove is an electronic device equipped with different types of sensors to sense the finger flexion or contacts in real-time. It can be used to grasp, move and rotate the objects in a virtual scene. Current products have been able to detect finger bends and utilize magnetic position sensors to locate the hand position in three-dimensional space. The popular gloves available in the market are shown in Fig. 2. Glove based systems can be used more

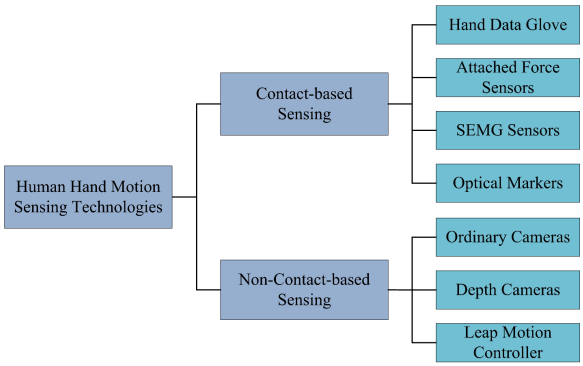


Fig. 1: Human hand motion sensing technologies.

in the hand motion animation, and they can successfully work with multiple degrees of freedom (DOF) for each finger, because of the characteristics of high accuracy, high response speed, and strong operability.

Luzanin *et al.* developed a data glove-based hand motion recognition system using a probabilistic neural network trained on a cluster set generated by a clustering ensemble [26]. In this system, a low-budget data glove with 5 sensors was used to efficiently recognise the hand motions in VR applications. Cai *et al.* provided a gesture recognition method based on a wireless data glove [27]. This system selected the CC2530 chip as the main control chip, and used the Xsens MTi sensor to acquire glove data through four fingers buttons, and finally realized the wireless communication by using the RS232 serial interface. In other related work [28]–[31] and the aforementioned articles, it is proved that the data glove is an effective way to capture the hand movements, however, due to the differences in hand sizes, how an optimal calibration to settle the mapping from raw data to real finger joint angles of different hands, is still a main challenge. Moreover, the data glove will obstruct the object-hand interaction by reducing the flexibility of the hand movements.

(a) DG5-V Glove (b) CyberGlove III (c) ShapeHand Glove

(d) VHand DGTech (e) 5-DT 14 Glove (f) CyberWorld P5

Fig. 2: Examples of data gloves available in the market.

2) Attached force sensors: The force control is the base of stable manipulation with a multi-fingered robot hand. A number of force sensors and several techniques for measuring exerted forces have been proposed by both the academic and industrial communities [32]. The most important design criteria of force sensors in manipulation tasks are the spatial resolution, robustness, sensitivity, and frequency response. Attached force sensors, which include four common force

sensing techniques, need to meet the demands on the object characterization, identification and manipulation [33]. Capacitive sensors obtain the displacement, force and speed based on the variation of distances between the upper and lower electrodes caused by external force changes. Piezoresistive sensors detect the changes in the resistivity of the sensing material formed on a silicon substrate. Piezoelectric pressure sensors use the piezoelectric materials to generate an electrical charge that is proportional to the pressure applied. Strain-gauge converts the amount of strain (pressure, tension, weight, *etc*) into the amount of change in resistance. TABLE. III shows the pros and cons of these sensors based on the recent contact-based hand motion sensing papers, as well as technical demonstrations.

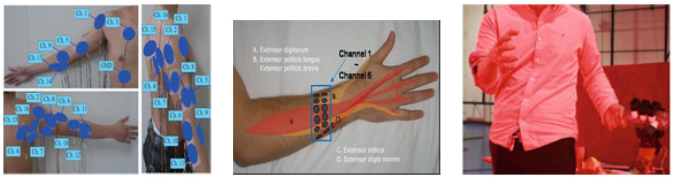
TABLE III: Pros and cons of different force sensors

Sensors	References	Strengths	Weaknesses
Capacitive	[34]–[38]	Good frequency response High spatial resolution A large dynamic range	Electro-magnetic noise Sensitivity to temperature Non-linear response
Piezoresistive	[39]–[44]	Low power consumption Simple integration High flexibility Long term stability	Hysteresis Fragility and rigidity Lower repeatability
Piezoelectric	[45]–[50]	High spatial resolution Fast dynamic response High spatial resolution High bandwidth Robust	Temperature sensitive Electrical junction fragility Drift of sensor output Not stretchable
Strain-gauge	[51]–[55]	Higher sensitivity Lower cost Small size	Non-linearity Not recover with overload Temperature & humidity sensitivity

3) Surface electromyography: Surface electromyography (SEMG) provides technical support for evaluation of the biofeedback of muscle movements by measuring the EMG signal on the surface of the skin [56]. By recognizing the certain muscle contraction patterns of the HHMs, the robot/system can identify the human's intention and perform corresponding actions or communication, such as completing hand motions through prosthetic hands. Examples of current applications of SEMG are shown in Fig. 3.

By obtaining users' motion intention with SEMG sensing, Kiguchi *et al.* presented a new method to realize the upper-limb control, for human-like manipulation [57]. Al-Timemy *et al.* classified various hand motions for the prosthetic control, and used an offline process to evaluate the classification performance based on multiple-channel SEMGs [58]. Hu *et al.* employed SEMG signal as a control feedback and the real-time SEMG motion recognition could be implemented for controlling the grasping of a dexterous hand [59]. Though SEMG sensors are a promising method for extracting electromyography signals to help the robot to simultaneous control wrist and hand DOFs, researchers need to pay more attention to some critical issues: how to resolve or reduce the effects of crosstalk, electrode displacement and information redundancy, and how to select/evaluate suitable features from the raw signals.

4) Optical markers: Optical marker based motion capture technique has been used to track and analyse the HHMs



(a) Electrodes position [57] (b) Electrodes view [58] (c) Teleoperation [59]

Fig. 3: Applications of SEMG sensors.

in a particular condition with calibrated cameras, which are applied to only track the markers placed on the human body. Fig. 4 shows some examples with optical markers. They can provide direct, reliable, accurate and fast joint positions, even in clustered scenes with varied lighting conditions, object occlusions, and insufficient or incomplete scene knowledge [60]. Kuo *et al.* provided a non-invasive tracking device based on skin sensors and surface markers for obtaining 3D quantitative measurements [61]. Metcalf *et al.* presented a kinematic model based on surface marker placement and used standard calculations to calculate the specified marker placements [62]. Optical markers can effective track the HHMs, but have been limited by kinematic protocols, such as marker placement errors caused by skin deformation and marker movements, as well as the requirements of the constrained measurement space, special-purpose cameras, and inconvenient markers or suits.

Fig. 4: Hand motion tracking using optical markers [60].

B. Non-contact-based sensing technologies

1) Ordinary cameras: Contact-based sensing techniques are limited by the complex connection wires, surface properties, hysteresis and sensitivity. The emergence of affordable commercial marker-less cameras is a potential new solution to avoid these drawbacks. RGB camera delivers the three basic color components (red, green and blue) on three different wires, and can obtain the color information through the color variation and superimposition captured from three independent CCD sensors [63]. It can easily achieve millions of pixels with above twenty frames per second, which provide a rich source and a high accuracy for detecting human motions. However, the human motions have high dynamics and the occlusion often occurs due to the perspective projection. In order to solve these problems and have higher accuracies, multiple RGB cameras separated with certain angles, are employed to observe 3D human motions in different directions.

Stereo camera consists of two same specifications of the digital camera. Through focusing, zooming and sensitising, the 3D structures of the subject are generated from different viewpoints. Stereo camera has fixed lens angles and internal pre-calibrations, which give the camera freedom of moving, but the angle between two lenses is usually too small to cover

the occlusion area in human motions. Additionally, due to the complexity of stereo geometry calculation, stereo intensity images are sensitive to light changes, so it is difficult to match correspondingly for triangulation.

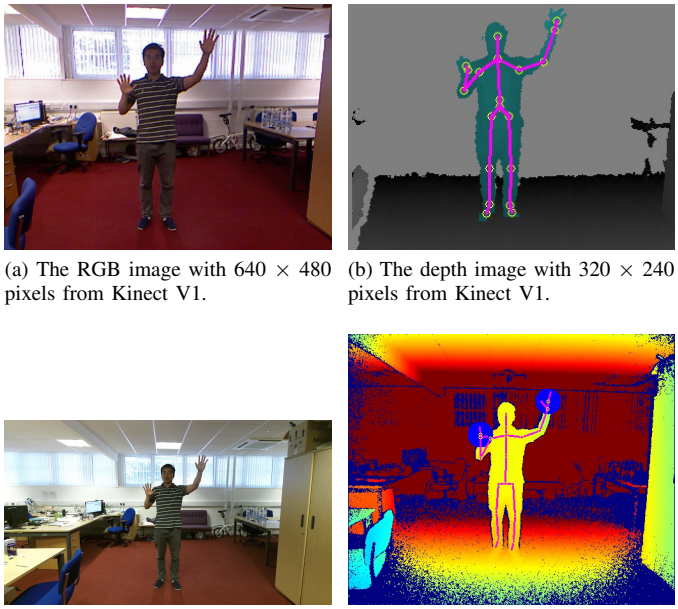
2) Depth cameras: Compared to the ordinary cameras, depth cameras are capable of capturing depth information, and they are much faster and easier to deploy a 3D vision system than the ordinary cameras on the analysis of HHMs. Time-of-Flight (TOF) cameras can be applied to evaluate the 3D structure directly without common computer-vision methods [64]. Oprisescu *et al.* proposed a TOF based automatic approach for recognizing some defined hand gestures [65]. Kopinski presented a scheme on 3D hand posture recognition based on TOF sensors in an outdoor environment [66]. Lower sensitivity to the light environment, miniaturization, and high effectiveness are the main advantages of TOF cameras, but low resolution is one major drawback.

Kinect as the most typical of depth cameras provides synchronised color and depth images. It has been widely used in computer graphics, video games, human computer interaction (HCI), object recognition, and computer vision [67]. Fig. 5 shows two versions of Kinect. In order to improve the sensing accuracy, the second version was released in 2013 with a higher specification than the first version. Real-time interaction can be achieved by 3D human motion capturing technologies without manipulating the controller [68]. Raheja *et al.* presented a Kinect based fingertip detection and centres of palms detection approach to recognize hand motions [69]. Frati *et al.* proposed a new solution based on Kinect technology to compensate for the lack of location awareness in contact-based sensors [70]. Depth cameras have apparent advantages, though it is still difficult to capture hand motions via a single depth camera in cluttered indoor environments. Moreover, it requires special lighting conditions and high contrasts, while noise and body occlusion can have a great influence on the acquisition of key information of the HHMs.

3) Leap Motion controller: Leap Motion controller is a new gesture and position tracking sensor, with sub-millimeter accuracy and repeatability for the HHMs controlled user interface [71]. In contrast to the depth cameras, this controller uses infrared optics and cameras instead of the depth sensors, and the above-surface sensor is used in the realistic stereo interaction systems compared to the standard multi-touch solutions. Chen *et al.* proposed a hand gesture based robot control system using the Leap Motion controller, and realized the function of controlling virtual universal robot UR10 with hand gesture through the mathematical process [72]. Mapari *et al.* presented an Euclidean and Cosine based Indian sign language recognition system to recognise the positional information of the HHMs using the Leap Motion sensor [73]. The Leap Motion controller can recognise and track the HHMs accurately, but the capture system can only be used in a specific space, and the results are limited to what can be performed within the capture volume without extra editing of the data.

IV. Hand Motion Analysis Methods

Once the multi-sensory hand motion information has been captured from the sensing devices, it is necessary to distinguish different categories among the information by using a classifier. TABLE IV contains six common approaches for the hand motion classification. Next, the detailed presentation and discussion of these obtained techniques will be explained.



(a) The RGB image with 640 × 480 pixels from Kinect V1.

(b) The depth image with 320 × 240 pixels from Kinect V1.

(c) The RGB image with 1920 × 1080 pixels from Kinect V2.

(d) The depth image with 512 × 424 pixels from Kinect V2.

Fig. 5: Kinect Version 1 vs. Kinect Version 2 in RGB and depth images [68].

A. Support Vector Machine

Support Vector Machine (SVM) is a novel large margin classifier used for classification and regression, which is effective in a high dimensional space and compatible with different kernel functions specified by a decision function. SVM is a kind of raised optimized questions from that and its solution has the characteristic of overall optimum, as well as the stronger generalization ability. Liu *et al.* evaluated and verified the hand gesture recognition results in a driving license test based on SVM [74]. Chen *et al.* presented a SVM based robust visual system for hand gesture recognition in finger guessing games [75]. Dardas *et al.* used bag-of-features and multiclass SVMs to recognize the hand gestures [76]. These research results prove that SVM can effectively identify the hand motions, and have a satisfying recognition accuracy. However, the long training time makes it difficult to solve the real-time problem from the memory size for training large data, and the suitable parameter selection is another challenge. In addition, if the hand motion classes are not linearly separable, selection of the appropriate kernel functions, such as polynomial, sigmoidal and radial-basis, is crucial to the performance of the hand motion recognition.

B. Neural Networks

Neural networks (NNs) are an information processing system for analysing time-varying data. They can handle very complex interactions compared with other methods, like the inferential statistics or programming logic [77]. NN uses the node as its fundamental unit, the links as its associated

TABLE IV: A summary of hand motion analysis methods

Algorithms	Sensory styles (contact or non-contact)	Motions (simple or complex)	Size	Accuracy	Previous research	Advantages and Disadvantages
SVM	Both	Both	Large	95%	Extensive	***Advantages:*** High performance higher generalization ability ***Disadvantages:*** Only handles binary classification Long training time
NN	Both	Both	Large	98%	Extensive	***Advantages:*** The mature and applicable technology With adequate training, high accuracy can be achieved ***Disadvantages:*** Time consuming Needs retraining if hand gestures are added or removed
HMM	Both	Both	Large	93%	Extensive	***Advantages:*** Simplicity and reliability High accuracy with adequate training ***Disadvantages:*** Time consuming Difficult to observe the internal behavior
GMM	Non-contact	Both	Large	92%	Moderate	***Advantages:*** Fast convergence Stable and high computationally efficient ***Disadvantages:*** The local optimum problem of extremum
TM	Both	Simple	Small	97%	Extensive	***Advantages:*** Simplest and high accurate technique to implement Requires only a small amount of calibration ***Disadvantages:*** Do not have rotation invariance and scale invariance Overlapping templates for large motions
DTW	Both	Both	Moderate	96%	Minimal	***Advantages:*** Conceptual simplicity and robust performance ***Disadvantages:*** Quadratic cost Lack of feature weighting mechanism

weights, activation function such as the step, sign, and sigmoid functions as the transfer function [78]. By utilizing a neural network-based approach, Hasan *et al.* built a unique multilayer perception for recognizing hand gestures, then the given hand gesture data was finally classified into the predefined gesture classes [79]. Bouchrika *et al.* introduced a wavelet network classifier and a NN classifier learning algorithm to realize the interaction with the computer by hand gesture recognition [80].

To model more complex and high-level abstractions or structures from the training data, deep neural architecture has been proposed, following the recent achievement of NNs. Due to more hidden layers and the huge advantage of processing large data, it discovers an intricate structure by applying the BP algorithm, and creates a more abstract high-level representation of attribute categories by combining lower-level features [81]. Many future deep learning NNs such as deep NNs, convolutional deep NNs, deep belief networks and recurrent neural networks will take into account that it costs energy to activate neurons and to send signals between them [82]. Compared with the traditional NN methods, if deep learning NNs are used for recognition of hand gestures, the recognition accuracy and efficiency will be greatly improved.

C. Statistic approaches

This category contains two common techniques of hand motion recognition, including the Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs).

1) Hidden Markov Models: HMMs as a kind of stochastic state machine have been widely and successfully used in the automatic speech recognition [83], the nature language processing [84], and genomic sequence modeling [85]. HMM is a double stochastic process - a certain number of hidden markov chain and a set of random functions. It contains a hidden layer and an observation layer. The probabilistic link between the hidden and observed states can be equivalent to the likelihood that particular hidden state will create an observed state. It learns to weigh the important hand-shape information for detection and classification, determining the correct number of states for each motion to maximize the performance. In [86], HMMs were applied to recognise input gestures and improve the accuracy by using a real-time hand tracking and extraction algorithm. Wang *et al.* presented a HMMs based method to achieve automatic hand gesture online recognition and it successfully rejected atypical gestures [87]. HMMs have the advantages of being modeled directly and efficient mathematical analysis of processes and results. However, this algorithm is expensive both in terms of memory and computer time. Moreover, it is difficult to choose an optimal HMM for a given set of training sequences in a larger model.

2) Gaussian Mixture Model: Gaussian Mixture Model (GMM), which measures the Gaussian component densities

between parametric and nonparametric density models and estimates all GMM parameters, is well suited for biometric system, including object tracking, feature selection, background subtraction and signal analysis [88]. A real time vision system for hand gesture recognition based computer interaction was presented in [89]. GMM was mainly applied to acquire the foreground from the video sequence, and extract the extreme points from the segmented hand through star skeletonization. Lin *et al.* detected the skin candidate regions on the colour image with a GMM skin model for hand gesture recognition [90]. These examples and some more applications show that GMM is a reasonable and effective measurement method for hand motion capture and recognition. However, more components are required when fitting the datasets with nonlinear manifolds, because the intrinsic linearity of the Gaussian model leads to a relative large fitting error. How to reduce the computational cost in the optimization and how to design online learning strategy are the main focus of the current research.

D. Template Matching

Template matching (TM), which measures the degree of similarity between two image sets that are superimposed on one another, is widely used in object recognition, stereo matching, feature tracking, *etc*. Based on the characteristics of a high accuracy and a light calibration required, it is an efficient and effective approach to characterise image features. In general, it consists of two steps to recognise the hand motions. First of all, by collecting the data values for each motion in the original data set, the new templates are created. Secondly, by comparing the current sensor readings with the given set of new templates, the motion template which most closely matches the current data record is found [91]. There are several good examples of the template matching comparison, such as chaotic imperialist competitive algorithm [92], pixel rearrangement [93], orthogonal distance fitting [94], and steganography algorithm [95]. Because of the inherent drawback of computing all similarity values for matching all possible positions, template matching will lead to excessive time consumption, as well as lower efficiency. The focus of further work is the matching optimization problem, specifically how to realize the real time hand motion recognition.

E. Dynamic Time Warping

Dynamic time warping (DTW) is a well-known technique to find an optimal alignment between two given (time-dependent) sequences under certain restrictions [96]. Due to the performance of conceptual simplicity and robustness, DTW is being widely used to match the hand motions. Moreover, another advantage of DTW is that it does not require training but good reference patterns. Sempena *et al.* chose exemplar-based sequential singlelayered approach using DTW for some common human hand gestures [97]. Ko *et al.* proposed a robust and efficient framework that used DTW as the core recognizer to perform online temporal fusion on either the raw data or the features [98]. Because of the importance of reliable reference sequences in DTW, it appears that in some cases, the analysis of the angles needs a more accurate classification to recognition different gestures. The quadratic nature of space and time increases the computational complexity from another aspect. Because DTW finds the best path based on dynamic programming, it is very important to adaptively constrain the temporal warping while computing the temporal alignment. How to optimize the current method or adopt more advanced approaches, which allow an efficient and flexible alignment between two or more multi-dimensional time series of different modalities, is of great academic significance.

F. Others

In addition to six approaches described above, the Finite State Machines [99], Empirical Copula [100], Haar-like Features [101] and some variants from GMM and NN such as Fuzzy Gaussian Mixture Model (FGMM) [102], Bayesian Neural Network (BNN) [103] and Time-Delay Neural Network (TDNN) [104], have appeared in the journals and conferences. These novel methods can analyse the hand motions effectively and recognise the hand gestures successfully. Although only fewer references present these methods, it forms a new research direction.

V. Multimodal Hand Motion Sensing & Analysis

A. Multimodal motion sensing

Multimodal sensing technologies such as multi-sensor data fusion can merge rich information obtained by multiple sensors to achieve more accurate perception. Fig. 6 shows the general flow of information from each type of sensors based on [105], [106]. The types of multimodal sensing systems, which present the measurement method selection of each modality and the integration of different sensors, will be discussed in detail in the following.

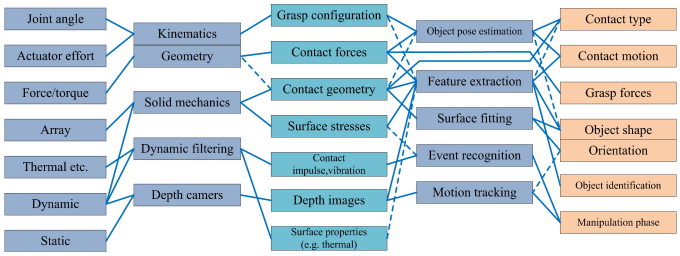


Fig. 6: Force-based and vision-based sensing information flow and signal processing.

1) Contact-based sensing: The combination of multiple contact-based sensors can acquire more information and avoid the drawbacks of a uni-type sensor. Current multimodal tactile sensing systems usually include tactile pressure sensing array, proximity sensors, dynamic tactile sensors, and thermal sensors. Tactile pressure sensing array typically consists of individual pressure sensitive elements attached on the surface of fingers. Wireless sensing based proximity sensors are mainly used for target region tracking. Dynamic tactile sensing includes several types of typical sensors, such as detection sensors, accelerometers, strain rate sensors, actively stimulated sensors and other sensors with fast response. Thermal sensors mainly detect the feature information related to temperature and humidity based on the temperature variation.

Ju *et al.* proposed a generalized framework integrating multiple sensors to analyse multimodal information based

HHMs as shown in Fig. 7 [107]. First of all, the information of finger trajectory, contact force, and EMG was captured simultaneously, and then transferred into the computer by using digital signal processor. Empirical Copula was applied to verify the correlations of sensory information in the pre-processing module. Finally, in-hand manipulations and grasps were recognized by utilizing FGMMs and the SVMs, and experimental results showed a higher recognition rate. Wettels *et al.* proposed a multimodal sensing scheme to capture the finger trajectory for gesture recognition [108]. BioTac finger-shaped sensor array was used to obtain the information of contact force, microvibration and thermal fluxe. Adaptive neural network was used to estimate the force sensing, mechano-electrical transducers attached on the surface of skin were applied to acquire the vibration sensing, and principal components analysis (PCA) was used to extract the relevant variant features for objects thermal sensing. The experimental results presented the validity and feasibility of multimodal sensors integrated into a device, thus prosthetic hands could identify and manipulate objects well based on the sensing package.

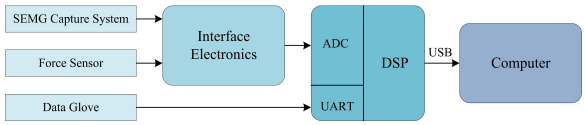


Fig. 7: Framework of multiple-sensor integration for HHMs analysis [107].

Contact-based multimodal sensor systems will be crucial for interaction based control improvement, better efficiency, better determination and objects recognition. There is thereby an urgent, but it is still a significant challenge, to reduce the users' discomfort with data glove or various attached sensors, to decrease the complexity of the circuit and so on. Improving and optimizing these problems will be one of the future works.

2) Non-contact-based sensing: In recent years, the introduction of vision-based sensors has opened new opportunities for hand motion recognition. The very informative description of three non-contact based sensors has been discussed above. With the drawbacks of contact-based sensing, researchers have attempted to recognise hand motions from the data obtained by non-contact based sensors.

Marin *et al.* proposed a novel hand gesture recognition framework to analyse the hand motions as shown in Fig. 8 [109]. The attributive characters of hand gestures were extracted by using Leap Motion and the corresponding depth information obtained based on Kinect. Kinect based depth map could provide other important information missing in the Leap Motion output. With the help of complementary data information of multisensor, a set of more perfect features based on the positions and orientations of the fingertips were identified and fed into a multi-class SVM classifier to recognise the preformed hand motions.

An effective hand motion recognition framework based on multiple depth was introduced in [110]. Hand region was firstly captured based on the depth and color information by using background exploiting. By using PCA and circle fitting, the feature sets of hand gestures, including the features

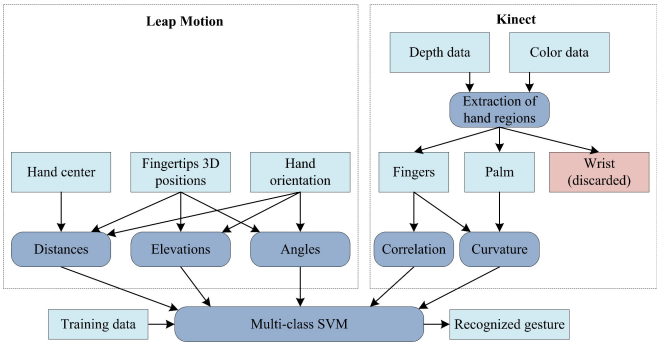


Fig. 8: Hand gesture recognition scheme [109].

of distance, elevation, curvature and palm were extracted. These combined features could effectively supplement the lack of information in the incomplete or certain gestures. Finally, a multiclass SVM algorithm was used to recognize the performed gestures. The experimental results confirmed that multiple sensors based hand gesture recognition could obtain a better performance by further adding the elevation and area features.

From the literature, the combined use of different sensors allows to provide richer visual information than each of the three types of sensors alone. The experimental results show that these proposed schemes have higher accuracies on standard datasets or experimental data obtained, thus providing hand motions evaluation with ample raw features. Further research may focus on the joint calibration of combined devices based on multiple sensors, as well as the recognition of more complex dynamic motions.

3) Mixed sensing: Considering the discussion of two types of multimodal motion sensing techniques, the integration of them looks like a promising substitution to provide a complementary strategy.

Contact-based multimodal sensors capture the complex motions of the human hands accurately through physical contact, while non-contact-based multimodal sensors acquire the information of HHMs against the influences of skin conditions. Current multimodal sensors integration refers to the combination of the same kind sensors based on their characteristics with or without contact, so there are few articles to describe the combination of the two different types of multimodal sensors for HHMs. The following are the key issues for mixed sensing:

- Data synchronisation: The integration of two types of multimodal sensors requires an efficient tool to acquire, process and send raw synchronised information.
- Exploration: By using the depth camera to detect the hand movements with data glove, the accuracy of spatial resolution will have a great improvement.
- Data fusion: Vision-based sensors acquire the HHMs information in the 3D space for distinguishing the finger joints and tracking their movements. Contact-based sensors obtain the given property through physical contact, and capture the hand movements. How effectively to fuse the data of these two types will bring a core difficulty.

However, most current multimodal sensor integration technologies just simply employ two or several types of sensory systems to obtain data for off-line analysis. The next step

in this direction should be the implementation of the data fusion and the signal processing algorithms, which predict user intention and control reaching and grasping movements based on a multimodal feedback [111].

B. Multimodal motion analysis

To facilitate the rapid recognition of the hand motions, various methods are presented and discussed in the above sections. Single method can recognise the specific hand movements and show good results, but they maybe not effective for complex hand motions. Some researchers try to combine some of the methods for multimodal analysis of the HHMs, so as to make up the drawbacks of the single method.

A set of recognition algorithms, including time clustering, fuzzy active axis Gaussian mixture mode, and fuzzy empirical copula, were presented to recognise different hand grasps and manipulations, which simultaneously processed the information of finger angle trajectories, hand contact forces, and forearm EMG [112]. The new framework combining three algorithms provided a feasible solution for HHMs recognition in a wide range of hand scenarios. Time clustering could identify accurately the start point and end point of the motions, and achieve a relatively high recognition rate. Fuzzy active axis GMM was capable to fast model nonlinear datasets as abstract Gaussian patterns, and recognise the testing motions. Fuzzy empirical copula was applied to recognise HHMs by the use of the proposed novel motion template and recognition algorithm. Song *et al.* proposed a method of gestures recognition based on GMM and HMM. Kinect was applied to extract human's skeleton information for the 3D position data of joints firstly. The features were extracted by preprocessing the samples for each gesture. Finally, GMM and HMM were used to model and segment gestures from the real-time data flow, and recognize the motion gestures [113]. Rashid *et al.* presented a framework for the integration of gesture and posture recognition systems at the decision level to extract multiple meanings. Firstly, based on the Gaussian distribution and depth information, 3D information was exploited for segmentation and detection of gestures and postures. Then, feature vectors were extracted from statistical and geometrical properties of the hand. Finally, HMM and SVM were used to train, classify and recognize both gestures and postures [114].

Compared to the single method for hand motion analysis, the confirmed results of multimodal motion analysis present higher accuracy and a better coordination. This strategy is intended to provide a feasible solution for recognizing various hand movements. However, there are not enough papers about it in the related science journals. This new research direction might be attracting more interest in recent years.

VI. Applications

A. Human computer interaction

Compared to the traditional way of mouse and keyboard, hand motions provide an attractive and natural approach for HCI. In the last decade, vision-based HCI and sensor-based HCI have been developed in a high speed, along with the development of HHM sensing techniques. For vision-based HCI, multi-camera, Kinect and leap motion controller are the main technological means for hand motion recognition, and the VR technology makes the interaction between human and computer more natural and more advanced. Sensor-based HCI methods mainly include tactile sensor, pressure sensor and motion tracking sensor [115]. These advanced techniques can realize the virtual mapping of real actions by acquiring feature information of HHMs, and be applied to the medico-surgical dexterous manipulation [116]. The future direction is the research of wearable computer, stealth technology, immersion game and other motion recognition techniques, as well as the VR, remote controlled robot, telemedicine and other tactile interaction techniques. Another direction is to improve the hardware device recognition accuracy, sensitivity and robustness.

B. Hand gesture recognition

Hand gesture recognition consists of gesture spotting that implies determining the start and end points of a meaningful gesture pattern from a continuous stream of input signals and, subsequently, segmenting the relevant gesture [117]. The initial attempt at recognizing hand gestures is mainly to detect the joint angles and spatial locations of the hand by using machinery equipment, such as the data glove. With the rapid development of the computer vision technology, hand gesture recognition is playing an increasingly important role in the smart home, intelligent vehicle, VR/augmented reality (AR), *etc*. Fig. 9 presents the key flow of hand gesture recognition via cameras. At present, most researchers focus on the final recognition of gestures. They first simplify the gesture background and utilize the algorithm to segment the gestures in a single background, and then use the common recognition methods to analyze the meaning of gesture expressions through the system analysis. In practical applications, the acquisition of gestures is usually in a variety of complex environments, like the conditions with different illuminations and changes of distance between gestures and collection equipment. Hence, the gesture recognition will continue to be the focus by scientists as a hot research area and promote the rapid development of related core technologies such as multi-steady-state perception.

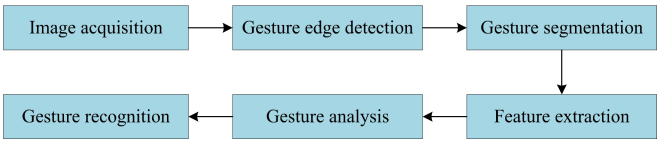


Fig. 9: Hand gesture recognition flow chart.

C. Multi-fingered robot manipulation learning

So far, robots have been very successful at manipulation in simulation and controlled environments. The application of robots has been gradually expanded from the traditional industrial field to the fields of nuclear energy, aerospace, medicine, biochemistry and other high-tech fields, as well as home cleaning, medical rehabilitation and other service areas. These emerging areas require the multi-fingered robot manipulation to meet the force closure criteria, in order to achieve the human-like manipulation, such as stable grasp for different objects. There are three key techniques for multi-fingered robot

manipulation learning, that is, the optimal grasp planning, grasp force planning and multi-fingered control [118]. Some issues, like real-time constraints, sensory variation, noise and clutter, need to be considered to realise robust manipulation. Hence, the main research content is to investigate effective approaches and practical solutions via multimodal data fusion and corresponding techniques, and design the control strategies integrated with human manipulation skill models and online learning capabilities.

D. Prosthetic hand control

More recently, small sized prosthetic hands have been developed, such as Shadow Dexterous Hand [119], DLR/HIT Hand II [120], iLimb hand [121], Robonout hand [122] and so on. The advanced prosthetic hand technology is being used to provide amputees with enjoyable normal lives. While the recent prosthetic hand technique has developed by leaps and bounds, the main goals of the prosthetic hand control include human sized robotic hand with enough functionalities, fast and stable skills of grasping and manipulation, selection of best grasp position, and versatile [123], [124]. Future research will include integrating the technologies to increase the power and reduce the weight for a wearable prosthesis, and developing a simpler and cheaper tactile sensor intended specifically for contact detection. One trend of further research is to design the hierarchical human hand manipulation database based on multimodal data, develop approaches to generate finger trajectories and force distributions based on the derived skill models, and further to use them to control the prosthetic hands.

VII. Discussion and Conclusion

As one important research topic in various applications, HHM analysis is attracting broad interest in robotics. Two types of the natural HHMs are proposed through the analysis of the current hand motion strategies. In order to realize the human-robot manipulation skill transfer, various sensing techniques in the last decade were used to acquire the information of HHMs, such as the dynamic movement trajectory of finger joints, and the dynamic distribution of finger force. Developments of sensing technologies have been summarized and discussed, as well as their applications, current challenges and tendency of future research.

A rapid development of the biomimetic material processing, 3D visualization technology and nanotechnology have resulted in the development of a range of low complexity, and high reliability sensors. In this paper, the current sensing techniques have been presented in detail with two major categories based on their characteristics of raw data collection. Continuous developments in the fields of material engineering, nanotechnology, fabrication technologies and 3D vision technique lead to advances in sensor performance, as well as reliability and mechanical properties [125]. In this paper, the sensing techniques such as the hand data glove, attached force sensors, SEMG, optical markers, ordinary cameras, depth camera and Leap Motion controller have been presented in detail. These sensory systems are divided into two major categories based on the contact. How to extract useful mathematical quantity, and then recognize the corresponding motions are very important steps for the HHMs analysis. Because of the complex hand movements, some sensing information, such as contact point, finger swing angle, and position change, need to be taken into account in the future. Current various hand motion analysis methods for recognizing the motions and achieving the skill transfer are presented and discussed in Section IV. This category contains six of the most common approaches for HHMs recognition, and their related characteristics are described and compared. In addition to these commonly used algorithms mentioned, some novel algorithms and variants have also been adopted in some literature.

From the review of the current sensing techniques, it's now generally agreed that multi-sensor integration is the best approach and the predominant choice to the HHM analysis. A tendency of the multimodal sensing is to take full advantages of the multi-sensor integration techniques with respect to the structure, gesture movements and physiological properties. Three multimodal sensing methods are presented, namely, contact-based sensing, non-contact-based sensing and mixed sensing. For the contact-based multimodal sensors, what calls for special attention is the integration into a real robotic system. How to reduce the amount and complexity of wiring and cross-talk for the improvement of robustness is still a challenge. Moreover, utilizing the non-contact-based multimodal sensing methods, for example vision-based sensing techniques, is another good choice. Although this method has many advantages, it is still facing some shortcomings, such as distance, lighting conditions and limited relevant points. The mixed sensing method means the combination of contact-based sensors and non-contact-based sensors. In addition to the existing problems of the above two mentioned approaches, some key issues such as synchronisation, exploration and data fusion, need to be paid more attention. Few articles are found to describe the combination of these two types of multimodal sensors. According to the detailed classification and description of the multimodal motion sensing technologies, the state-of-art sensing hardware may face the limitation of dimensions, distributions and functionalities. The multimodal sensor integration system will improve the capability of HHMs acquisition and analysis, and avoid the drawbacks of individual sensor. Based on more complete and abundant data information, it needs an effective solution with several hand motion analysis methods to recognize different hand movements, like in-hand manipulation. The confirmed results from the related papers present the higher accuracy and better coordination than the single methods. Based on the multimodal sensing approaches integrating various sensor techniques with the developed algorithms, researchers are able to build a versatile and adaptable platform for HHM analysis, and thereby overcoming the limitations of the sensing hardware, and having wider applications especially in the HCI, hand gesture recognition, multi-fingered robot manipulation learning and prosthetic hand control, are the main future research directions.

Although the developed multimodal sensing technique has reached quite a level of maturity and has achieved satisfactory results, the various available sensors can provide only a fraction of the needed topic sensing information sets (*e.g.* limited force range, insufficient spatial and temporal resolution,

limited sensing area and limited capability of sensing shear forces). A truly reactive manipulator with multiple sensors fusion for HHM recognition can achieve advanced human-like manipulation tasks based on the satisfactory sensory information. The future work will be focused on the creation of hand motion database, the encoding of sub-actions and finger primitives, and further transferring these skills into bionic multi-fingered dexterous hands, thus providing intelligent robot with powerful capabilities of experience accumulation and online learning, for autonomous and adaptive complex manipulation.

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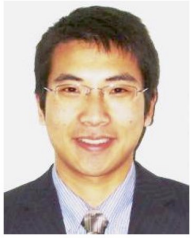

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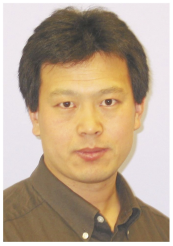

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