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A Survey on Gesture Control Techniques for Smart Object Interaction in Disability Support

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Abstract— *With an estimated one billion people worldwide experiencing disabilities, there is a growing imperative to develop assistive technologies that enhance accessibility and independence. There have been tremendous improvements in helping the disabled, thanks to the results of numerous studies. Gesture control offers a promising avenue by allowing users to interact with smart objects using natural hand movements, thereby overcoming physical limitations. With the aid of a gesture detection and control system, the user is able to move any object in the direction he chooses, greatly reducing the need for human intervention in the majority of daily tasks requiring physical movement. This survey paper provides a comprehensive overview of gesture control techniques utilized in smart object interaction for disability support. The research systematically reviews existing literature on gesture control techniques, encompassing various modalities such as vision-based, wearable, and sensor-based approaches. Additionally, it explores the application of gesture control in a range of assistive devices, including wheelchairs, robotic arms, and smart home systems, tailored to meet the diverse needs of individuals with disabilities. Furthermore, the paper examines the challenges and limitations of current gesture control systems, along with emerging trends and future directions in the field. Through this survey, insights are provided into the state-of-the-art technologies, promising advancements, and the potential impact of gesture control in empowering individuals with disabilities to lead more independent and fulfilling lives.*

Keywords— *Assistive Technology; Disability Support; Human-Computer Interaction; Gesture Recognition; Wearable Devices.*

I. Introduction

Due to mishaps, age, or illnesses like cerebral palsy and spinal cord injuries, there are currently 1 billion people, or 15% of the world's population, who are disabled [1]. These impairments profoundly impact individuals' ability to perform everyday tasks independently. Among these individuals, elderly and partially handicapped individuals often encounter significant challenges in moving objects as part of their daily routines. The inability to independently manipulate objects can severely impede their autonomy and quality of life, highlighting the critical need for improved assistive technologies tailored to address their unique needs.

In recent years, there has been a growing recognition of the role of technology in mitigating the challenges faced by individuals with disabilities. Specifically, employing technology to assist in object movement holds immense promise in enhancing the independence and mobility of elderly and handicapped individuals. By leveraging innovative solutions, such as gesture-controlled systems, individuals can interact with smart objects using intuitive hand motions, thereby reducing the reliance on physical intervention and facilitating greater autonomy in daily activities. Despite the advancements in assistive technologies, current solutions for object movement still present significant limitations, particularly in the realm of gesture control. While gesture-controlled systems offer a promising avenue for facilitating object manipulation, existing designs often suffer from inefficiencies and usability challenges. These limitations stem from factors such as limited accuracy, reliability, and adaptability to diverse user needs and environments [2]. Consequently, there is a pressing need for more efficient and user-centric designs that can effectively address the complexities of object manipulation for elderly and partially handicapped individuals.

In light of these challenges, this paper aims to explore and evaluate the landscape of gesture-controlled systems for smart object interaction in disability support. By conducting a thorough review of the current literature, we seek to identify the strengths, weaknesses and new trends in motion control technologies. Through this analysis, we endeavour to shed light on the current state-of-the-art, pinpoint areas for improvement, and propose recommendations for the development of more effective and inclusive assistive technologies. Ultimately, our goal is to contribute to the advancement of gesture-controlled systems that empower elderly and handicapped individuals to lead more independent and fulfilling lives.

This paper is organized as follows: Section II details the background of the study, Section III describes existing assistive technologies for object manoeuvring, provides a review of recent literature on gesture based detection and control systems, addresses the limitations and discusses potential future advancements or improvements in technology that could further enhance these systems for better usability and efficiency, followed by conclusion in Section IV.

II. Background

The market is seeing a steady stream of innovation in smart home appliances due to the Internet of Things' (IoT) rapid development. There is a growing public need for convenience and safety in residential areas. Meanwhile, the average lifetime of people is steadily rising due to advancements in local medical technology and quality of life. But ageing societies are an issue for nations all around the world. In the domains of robotics, medical applications, and gesture control, hand gesture recognition is becoming more

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and more common. Thus, the goal of numerous studies has been to develop a smart and easy-to-use home appliance control system for the elderly or disabled. The advancement of computer technology created a demand for genuine human-machine communication. Despite using touchscreen technology, our new mobile devices are too expensive to be installed on desktop computers. Although the mouse is a highly helpful tool for operating the system, those who are not used to using a mouse for interaction or who have physical impairments may not want to use it.

Hand gestures can be divided into four categories: manipulative, conversational, controlling, and communicative [3]. Because sign language is so highly structured, it is utilised as a test-bed for vision algorithms, making it an essential example of a communication gesture [4]. Simultaneously, sign language facilitates easy computer interaction for individuals with disabilities. One kind of controlling gesture that focuses on research in vision-based interfaces (VBI) is the analysis of pointing gestures for the purpose of identifying virtual objects [4]. Another control gesture is the navigating gesture, which recognizes the orientation of the hand as in 3D and allows users to travel in virtual environments (VEs) with their hands rather than wands. The natural shape of virtual things can be interacted with through the manipulation of gestures. These kinds of motions have a variety of uses, including remote operation and virtual assembly. Psychological study is necessary because communicative gestures in human contact are deemed significant. On the other hand, these studies can benefit from vision-based motion capture approaches [4].

Generally speaking, there are two types of hand gestures: static gestures based on hand shape and dynamic gestures based on hand movements [5]. According to [6], "Posture is a specific combination of hand position, orientation, and flexion observed at some time instance" is the best definition provided by the authors for hand posture or static gestures. When making a static hand gesture, the posture remains unchanged over time, and the gesture's whole meaning can be deduced from one or more hand images recorded at a specific moment. "OK" and "STOP" are two excellent instances of this kind of gesture. A dynamic hand gesture is described as follows: "A gesture is a series of positions associated with movement in a short period of time" [6]. In this case, a series of postures, each specified by a different frame in the video feed, describe the dynamic gesture. "No," "Yes," "come here," and "goodbye" motions are a few examples of dynamic gestures. These gestures cannot be recognized without considering the temporal context information.

There's a new trend in communication between humans and technology. Numerous scholars have endeavoured to discover dependable and compassionate techniques for identifying hand gestures, facial expressions, and body language; among these, the hand gesture proves to be the most adaptable and practical. However, because of the hand's great flexibility, hand tracking and recognition tasks are difficult [7]. Still, there are a lot of issues with hand motion recognition. Their technology's inability to swiftly and precisely identify users' hand movements prevents it from instantly resolving consumers' issues [8].

III. Literature Review

In the middle of the 1980s, Krueger presented the first gesture-based interaction as a novel form of Human-Computer Interaction (HCI) [9]. By 2006, HCI had grown to be a prominent field of study. A hand gesture (or two) constitutes the larger category of gestures because the human body embodies multiple distinct hand-distinguished arrangements. Furthermore, hand motions are crucial to sign language.

A. *Current Approaches to Analysing Hand Gestures*

Getting the data required to complete a task is the initial step in any hand gesture recognition system. Currently, vision-based, data-gloves, and color-marker approaches are employed.

1. *Vision-based Approaches*

These methods [10], which use human motion captured by one or more cameras [11], and vision-based devices [Fig. 1], may manage a variety of attributes for gesture interpretation. Sensor-based methods do not have this. Despite the simplicity of these procedures, a number of obstacles may arise, such as varied lighting, a complicated background, and the existence of items whose skin tones are similar to those of the hand (clutter). Furthermore, the system needs to meet certain requirements such computing efficiency, speed, durability, and recognition time [12] [13]. The number of cameras, speed and response time, environment structure (including movement speed and/or lighting conditions), user requirements for wearables or non-wearables, low-level features like histograms, silhouettes, edges, moments, and regions, type of representation (2D or 3D), and time representation are some differences between vision-based techniques [14].

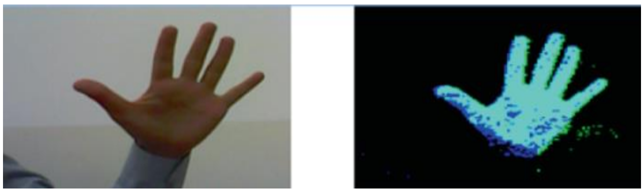

Fig. 1. Examples of input techniques for vision-based hand gesture recognition [15].

2. *Sensor-based Approaches*

As seen in Fig. 2, sensor- or data glove-based techniques use sensors to record the hand's position and motion. These methods make it simple and accurate to calculate the coordinates of the finger, palm, and hand configurations [13] [16] [17]. Because the user must physically connect to the computer, the sensors are unable to establish a simple connection with it. In addition to being costly, these gadgets are inappropriate for use in virtual reality environments [17]. Moore's Law predicts that over time, sensors will get smaller and less expensive. We think it will become more common in the future.

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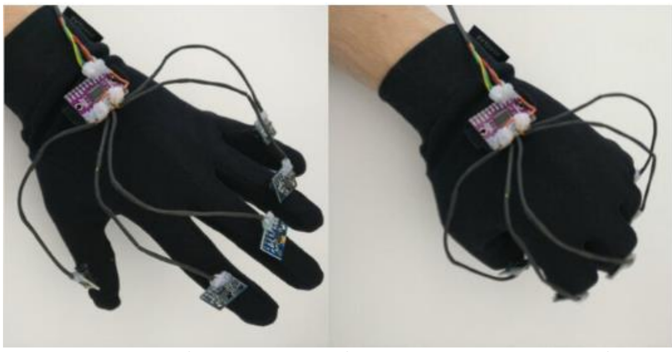

Fig. 2. Examples of input techniques for data-glove approach [18] of hand gesture recognition.

3. Colored-Markers Approaches

These methods make use of coloured gloves that are marked on a human hand to aid in hand tracking and to identify the fingers and palm. By removing geometric elements, marker gloves can be used to form the shape of a hand [19]. The author [20] showed the palm and fingers and a fur glove dyed in three different colors. In comparison to Sensor or Data Glove approaches, this approach is thought to be straightforward and reasonably priced [20], but it still falls short of achieving sufficient genuine human-computer interaction [19].

Fig.1. Examples of input techniques for coloured markers hand gesture recognition [21].

B. Tools used for Hand Gesture Recognition

The majority of current hand identification tools [22] are static, do not gather all the data, and while they can provide a clear image, they are not always accurate in their output. As a result, they perform admirably on some platforms but not all of them. The various techniques available for recognizing the gesture rely on methods that range from pattern recognition, computer vision science, statistical and dynamic modelling, picture processing, etc.

1. Finite-State Machines (FSM)

The authors of [23] presented a method for hand gesture recognition using an FSM. Four distinct stages of a general gesture can be represented by the machine's state alone: a static start position (fixed in a minimum of three frames), smooth hand motion, fingers and gesture's finish, a static end position in a minimum of three frames, smooth hand motion, and return to the starting position. This method compares the input gesture vector with the stored gesture vectors using vector displacement.

2. Fuzzy Clustering Algorithms

Li Xingyan presented a system in [24] that uses a fuzzy c-means clustering technique to identify hand gestures and is used in mobile remote controls. The image captured by the camera in this system is converted from RGB to HSV space colour. After a few pre-processing procedures like noise reduction, object removal, and thresholding, the next step is to extract the hand shape. Thirteen items make up the features vector; the first is the aspect ratio, which determines the bounding box of the hand. The remaining twelve values are utilised to describe the image's grid cells. The hand image's 3x4 block's average grey levels are represented by each cell. The FCM method is then used to classify the movements, with the average cell representing the brightness of the pixels in the hand image. This method is used in a variety of settings, including ones with complicated backgrounds and steady lighting. Six motions are made, and twenty language sample examples for each gesture make up the training database. The system's recognition accuracy rate is 85.83%.

The basic concept behind clustering algorithms is that they use measurements to separate the sample data into groups [25]. Due to their ability to combine complicated data sets into regular clusters, these methods are used extensively [25]. The fundamental distinction between fuzzy-clustering algorithms and other clustering algorithms is that the former may actually divide the sample of data into groups in a fuzzy manner, meaning that one pattern of data can belong for more than one set of data [17].

3. Condensation Algorithm

Based on the particle filter principle, the condensation method is primarily intended to follow the fast motion of items within the clutter [26]. Many different gestures may now be recognized using the hybrid mode of condensation algorithms, which is based on the temporal trajectories of the movements.

4. The Hidden-Markov Models

Before explaining the idea of Hidden-Markov models (HMM), which are Finite-State Automata in which the arc between the states carries a value indicating the probability, it is necessary to discuss Markov chains. The probabilities associated with the output arcs from a single state add up to a single value. Because the Markov chains are deterministic, there is only one arc that has a certain value when a state changes. The Hidden Markov model, which has one or more arcs contain the same value, can be used to get around this Markov-chain constraint [27]. Because the state cannot determine the sequence by looking solely at the output, HMMs are non-deterministic and referred to as hidden. A stochastic method is taken into account by the hidden Markov model [28] and contains a small number of values from Markov-Chain states with a collection of arbitrary functions. Speech recognition and sign language recognition both benefit greatly from it [29] [30] etc. Keskin [31] presented a system for recognising hand motions that used HMM for three-dimensional gesture recognition and real-time hand tracking. Two coloured cameras are utilised in this method to create three dimensions. Clutter is the system's difficulty, which the markers can help with. Schlenzig et al.'s approach [14] uses just one HMM to identify gestures. Static hand posture is represented by the observation symbols, while HMM states represent the movements. Since there are only three states and nine observation points in the HMM, there are only a few moves that can be defined in this system. To update the gesture estimations found using the knowledge about the current posture, this system employs a recursive filter.

HMMs are employed in both vision- and glove-based approaches, and it's critical to identify the hand's posture [32]. Studies have shown that the accuracy of HMM is very high, and it can identify many movements. Similar to ANNs, HMMs must be trained and must specify the precise amount of states for each gesture or posture in order to improve performance. The HMMS is the most effective alternative as a recognition technique when the kinds and quantity of gestures or postures are already pre-defined. The development process may take longer owing to retraining when hand postures and gestures are established throughout system development. One HMM needs to be retrained when the HMM was used for every gesture, as in Starner's work [29]; otherwise, the HMM for each gesture is only required to train the HMM for the new motions. The Hidden Markov model is thought to be the best method due to its high precision, which has reached over 90%, and extensive coverage in the literature. However, it requires a significant amount of training time and its hidden nature makes it challenging to understand what is going within.

5. Histogram-based Feature Recognition

Several studies have employed orientation histograms as feature vectors. The first orientation histogram application was put into place in a real-time gesture detection system by William and Michal [33]. They identified the gestures using the orientation histogram. The input video must be in black and white in order for the input images to be digitized. After certain conversions are made to determine each image's local orientation, the histogram is represented in polar coordinates by applying a blurring filter. There are two phases in the system: training and running. In the training step, the motions are saved along with their histogram in the training set. Calculate the features vector for the input image in the running stage, compare it to the features vector saved in the training stage, and use the Euclidean distance metric to determine who is closest to you. For every frame, the entire operation took 100 milliseconds.

Zhou et al. presented a system to recognize based on local orientation in the histogram in [34]. In order to extract a hand shape from the colour input image (RGB) and lessen the effect of illumination, the segmentation algorithm used skin colour. It then converted the colour space model to the HIS. H was given the picture L likelihood ratio in the HSI image. The hand region was divided using the threshold approach, and 128 parameters from the local orientation in the histogram were employed. The picture coordinates were added to the sub-window to reinforce the features vector, and k-means clustering was utilized to compress the vector representation of the features. During the recognition stage, the precise degree of matching between the input image's characteristics vector and the stored posture was determined using the Euclidean distance. The Locality-Sensitive-Hashing (LSH) technique minimized the computational cost required for picture recovery by roughly calculating the nearest neighbours.

Wysoski et. al. [35] presented a method for recognizing static gestures that are rotationally invariant using boundary histograms. Using a skin-color filter, morphological operations like erosion and dilation are carried out as a pre-processing step, and a clustering procedure is then utilized to find the groups in the image that share the same properties. The system has an invariance distance between the hand and the camera because the standard contour-tracking algorithm is used to extract the boundary for each group, divide the image into grids, and normalize the border's size. The boundary is represented by the chord's size chain applied on top of the homogenous background. The picture was divided into N sections, each of which was further divided into radial forms [35]. The feature vector contains an array of histogram features because the next step is to calculate the fringe chord magnitude histogram. This system employed dynamic programming (DP) and multi-layer perceptrons (MLP) for categorization. The system was able to identify 26 static postures from American Sign Language with success. For each posture, it took 40 pictures, 20 of which were utilized for training and 20 for testing. The system has two steps to increase or decrease the number of histograms from 8 to 36, as well as different resolutions for each histogram.

6. Artificial Neural Networks (ANN)

These kinds of methods are used to approximate functions for which a large number of frequently unknown inputs are received. They are modelled after and inspired by biological neural networks. Nodes are regarded as the central component of neural networks, much as neurons are the fundamental building blocks of the brain. Links with a weight represent a path to storage between the nodes. For instance, the back propagation technique uses the gradient descent idea to modify the network's parameters so that they better fit learning sets of input/output pairings. The effectiveness of ANNs in training data mistakes and their accomplishments in solving issues with speech recognition, visual interpretation, and Roberts Control methods. The majority of Artificial Neural Networks are implemented on sequential machines, while they can also operate in parallel machines if the devices are specifically made for ANN applications. Since artificial neural networks (ANNs) are inspired by biological neural networks, as mentioned earlier, there are problems that ANNs cannot solve or create. For instance, organic neurons create a complex temporal series of spikes, whereas artificial neural networks (ANNs) that construct their separate units have a single with a fixed value.

Numerous scholars looked into the recognition of gestures using neural networks. Most studies employ artificial neural networks (ANNs) to classify gestures, while some studies use ANNs to segment the hand. A mechanism for tracking hands is introduced in [36], while a system for NNs to recognize the Myanmar Alphabet Language (MAL) is provided in [37]. The system uses an Adobe Photoshop filter to identify the borders of the hand image. It then builds the input image's features vector by calculating the local direction histogram, which is then sent as input to supervisor NN. In [36], Stergiopoulou presented a system that uses SGONG Networks (Self-Growing and Self-Organized Neural Gas) to recognise static hand movements. Hand detection uses the YCbCr colorspace, while the SGONG network uses the competitive Hebbian learning algorithm for learning.

A network of neurons covering the hand object that takes on the shape of a hand is formed by using two neurons and continuing their growth. A method for identifying the Arabic Signe Language is offered by Maraqa [38]. There are two NNs in the system that are recurrent. The Elman network is employed (partially) in the fully recurrent and recurrent NNs separately. One layer of colour is segmented for the wrist and five layers are segmented for the fingertips using the data gathered from Colored-Glove and the HIS model of colours. Thirty features are taken out and grouped from a single image; fifteen elements are used to represent two different types of angles—one between the fingertips and the other between the wrist and the fingertips [38], and the remaining features are used to represent the distance between the fingertips and the wrist and fingertips [38]. This feature vector is valid for both NNs. There are 1200 colour photos total—900 for system testing and 300 for teaching. In terms of recognition rate, the outcomes were as follows: 95.11% for fully-recurrent and 89.67% for Elman-NN.

C. Recent Gesture Interaction Methods for Disabled People

Generally speaking, the primary goal of gesture recognition is to use mathematical methods for human-computer interaction and numerical linear algebra to interpret human gestures, such as hand and body movements. Motion detection can be divided into two main categories. Hand gesture is the first group. Body gesture recognition makes up the second group. A real-time robust gesture detection technique for hands was introduced by Kiliboz and Gudukbay [39] through interactive use of a six-degrees-of-freedom position tracker and a fast learning mechanism. It can assist in adaptively adding more new gestures to the collection of recognized gestures by gathering gesture data and learning through the process. However, because of the limitations of the hand gesture space, the number of hand recognized motions remains limited.

Furthermore, a method for recognizing hand gestures was introduced in 2015 [40] by the interactive use of the hand model and an extension of distance transform. Accurate and promising results are obtained when the method is computed and executed in real-time. Additionally, this study provides a number of exemplary hand motion tracking instances. However, the self-occlusion constraint of this strategy exists.

In recent years, a number of significant techniques for body gesture recognition have been proposed. For example, Kim et al. [41] developed a human pose gesture recognition system based on support vector machine (SVM). Afterwards, superpixels are employed to shorten processing times. It just makes use of depth data and runs on a single CPU (Central Processing Unit). As a result, this method's transportable platform—such as embedded surveillance boards—is both affordable and very useful. However, there is a restriction to this method when it comes to estimating body orientation throughout the human posture estimate procedure. Next, in 2015, Song and Davis [42] from Massachusetts Institute of Technology (MIT) developed a human-computer interaction method for continuous body gesture identification from an unsegmented input stream. Three-dimensional coordinates of body joints are continually calculated by a multimodal filtering method with a temporal sliding window. As a result, it can identify and follow body gestures from an infinite stream of information.

One potentially useful and engaging approach to assist those with impairments is through gesture interaction, which also includes hand gesture recognition. For those with special needs who are disabled, gesture interaction with the hands can be used to interpret sign language. A gesture interaction strategy for the hand was proposed by Luo et al. [43] in 2015, which involved merging two recognizers to ascertain the hand's sign language. For gesture interaction, the hand skeleton recognizer (HSR) and combinatorial approach recognizer (CAR) equation are used. The goal of this human-computer interaction research product is to help robots and people with disabilities identify automatically what messages they need to translate and communicate to the deaf community.

Using Viewpoint Feature Histogram (VFH) and sensor technologies, Sempere et al. [44] created a small robotic system for watching over the activities of disabled individuals with special needs at home. This system was built in 2015. This system consists of a low-cost RGBD sensor for hand gesture recognition and an adaptable interface with a motorised webcam. After then, this inexpensive robot is programmed and controlled via three-dimensional hand gesture interaction. Based on their investigation, they found that the technology works well for helping older individuals and those with physical limitations move around their home and watch things from a distance. Nevertheless, there are certain restrictions on how the behaviours and duties of the robotic system can be defined for this little robot. Furthermore, Premaratne [45] provided a useful summary of hand gesture inter-action techniques for reading and comprehending Australian Sign Language (Auslan) and American Sign Language (ASL) in 2014. Additionally, when utilising computer vision technology for sign languages, this work provided a clear description of a number of the primary difficulties associated with hand gesture detection from both static hand posture and dynamic hand movement.

In addition, Kirkham [46] presented wearable activity recognition research in 2014 with the goal of helping individuals with impairments by employing prosthetics to use sensor technologies to alleviate a variety of disability-related problems. It resembles assistive technology equipment in certain ways. A variety of sensors are included in this system for wearable computing systems. Moreover, this work offers some excellent illustrations of how the wearable activity recognition system is accessible. Through the use of sensor technology, wearable activity recognition system representative accessibility is used to assist individuals with physical disabilities by reducing a variety of symptoms associated to their condition. The goal of this project is to integrate the fields of disability discrimination law and wearable computers for activity recognition in a mutually beneficial arrangement.

Also, Gomez-Donoso and Cazorla [47] used computer vision to design a human-computer interaction prototype in 2015 that recognised Schaeffer's gestures, a condensed collection of motions created to benefit those with disabilities. Using this identification technology, it may identify body gestures and provide assistance to those with cognitive impairment by sending alarms to a disability carer. Nevertheless, the system has a disadvantage in that it can only identify a limited portion of the various gesture classes—11 in this work—despite being highly dependable and helpful for those with physical limitations.

IV. Conclusion

In conclusion, the development of assistive technologies that leverage gesture control has the potential to significantly enhance the accessibility and independence of individuals with disabilities worldwide. The research presented in this survey paper highlights the diverse applications of gesture control, ranging from wheelchair and robotic arm control to smart home integration, which can greatly improve the quality of life for those living with physical limitations. While current gesture control systems face various challenges and limitations, the emerging trends and future directions outlined in this work suggest that continued advancements in areas such as multimodal sensing, machine learning, and user-centric design will lead to increasingly robust and user-friendly assistive solutions. As the global population of individuals with disabilities continues to grow, the imperative to develop and refine gesture-based technologies that empower them to live more independent and fulfilling lives becomes ever more pressing. This survey paper provides a comprehensive overview of the state-of-the-art in this crucial field, serving as a valuable resource for researchers, technologists, and practitioners dedicated to improving accessibility and inclusion for all.

In summary, the key applications highlighted are wheelchair control, robotic arm control, smart home integration, and general object interaction - all of which can enhance accessibility and independence for people with disabilities through natural, gesture-based interactions. The key challenges and limitations highlighted in the study are related to the accuracy and reliability of gesture detection, the need for multimodal sensing, the importance of user-centric design, and the diversity of user needs and requirements in the assistive technology domain. By exploring the combination of gesture control with the various sensing modalities and technologies, assistive solutions could potentially offer users more intuitive, accurate, and versatile ways to interact with their environments and devices, ultimately enhancing their accessibility and independence.

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