Jurnal Kejuruteraan 37(5) 2025: 2537-2554
https://doi.org/10.17576/jkukm-2025-37(5)-38

Full Hand Pose Recognition and Clinical Assessment Under Dexterous Articulation in Activities of Daily Living for Tele-Rehabilitation: A Review

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Received 22 July 2024, Received in revised form 5 February 2025
Accepted 7 March 2025, Available online 30 August 2025

ABSTRACT

The rehabilitation of individuals who have suffered a stroke primarily relies on physical therapy directed towards enhancing the affected limb capabilities and mitigating lasting disability. Clinical assessment of a stroke patient is a critical step in determining the appropriate treatment and management of the patient's condition. The clinical assessment also helps to determine the severity of the stroke which can affect the patient's prognosis and the type of care that is needed. The dilemma with current clinical assessment in rehabilitation is that they are subjective and rely heavily on therapist's experience, which leads to inconsistency and do not directly quantify patients' ability to perform activities of daily living (ADLs). In this context, hand pose recognition and recovery estimation present significant academic and technical challenges due to complex structure and dexterous movement of human hands. This paper thoroughly examines the current research status of hand pose recognition and hand recovery estimation when performing ADL tasks, focusing on various types of hardware deployed for data collection. It carefully analyzes the advantages and drawbacks of hardware technologies and reviews the performances of different machine learning algorithms deployed. Furthermore, the clinical assessment tools were categories into four groups based on the evaluation methods. The current clinical assessments tools deployed in studies and utilized in stroke rehabilitation were reviewed. The summary of the existing research limitation and initiates a discussion on future research are provided.

Keywords: Hand pose recognition; hand recovery estimation; clinical assessment; machine learning algorithms

INTRODUCTION

Stroke is a disease with a significant burden due to the limb disability that it causes. According to the World Health Organization (WHO) prediction 2022, the aged population would increase by 73% in industrialized countries and by 207% overall by the year 2050(Mocan et al. 2022). This would likely lead to an unprecedented surge in aging-related motor impairment diseases such as stroke, multiple sclerosis, and neurological disorders (Bauer & Pan, 2020). Stroke remains a major health concern worldwide as it is one of the leading causes of disability and mortality, with 13.7 million new cases every year worldwide (Santamaría-Peláez et al. 2022). A larger percentage of stroke survivors are left permanently disabled, with complications such as motor, cognitive & language impairments, as well as psychological disturbances, increasing the demand for rehabilitation services. This impacts the patient's ability to perform activities of daily living (ADLs').

The recovery of the patient's motor function mainly depends on physical therapy aimed at improving the affected limbs functioning and reducing long-term disability. In general, there is supporting evidence indicating that physical rehabilitation methods integrating repetitive motor exercises can promote neuroplasticity and restructuring of the brain (Pan et al. 2021; Hughes et al. 2022). A key objective of the rehabilitation process is to oversee and assess the quality of a patient's movement and their utilization of the affected limb during everyday activities. Therapists presently gauge performance in activities of daily living (ADL) using diverse methods such as clinical observation, self-reported logs/questionnaires, and clinical performance assessments.

Self-report questionnaire asks the patient about their own motor function and ability to perform ADL tasks. Examples of the self-report questionnaire are the Health Assessment Questionnaire (HAQ) and the Activities of Daily Living Scale (ADLS) (Azri et al. 2024). In this article, we elaborate the performance-based assessment. The clinical measurement scale had been widely used to evaluate the motor functions of a stroke patient which includes the wolf motor function test (WMFT), motor assessment scale (MAS), Fugl-Meyer assessment scale (FMA), and action research arm test (ARAT) assessment scale to mention a few of the clinical assessment (Pan et al. 2021;: Angerhöfer et al. 2021). Nevertheless, this type of rehabilitation requires regular in-person sessions with therapists over several months, which can be challenging for countries with a shortage of professionals trained healthcare.

Moreover, financial limitations commonly prevent the therapy from attaining the frequency and intensity necessary for the maximal recovery of lost functionalities (Garzo et al. 2022). While medical scales demonstrate commendable reliability and validity, the findings rely heavily on subjective assessments by physicians, making it challenging to capture subtle functional improvements accurately. Consequently, certain poststroke patients may exhibit identical evaluation scores despite variations in their movement capabilities.

Tele-rehabilitation systems have the potential to offer an alternative to traditional rehabilitation service delivery. Tele-rehabilitation promotes frequent therapeutic exercise sessions, facilitating faster patient recovery (Rahman et al. 2023). Furthermore, it reduces the burden on physiotherapists and the need for more staff, as one therapist can manage multiple patients simultaneously (Radmanesh et al. 2021). Unfortunately, patients undergoing telerehabilitation are not able to assess their own functional state without a physician around(Rahman et al. 2023). Thus, personalized interventions that will maximize the improvements in patients' motor recovery cannot be reached, which has become a bottleneck for telerehabilitation (Yu et al. 2016). Furthermore, clinical assessments are measured based on various tasks and activities administered to the patients. Recognizing task activities remotely is essential for accurately evaluating the patient's recovery.

The organization of this review is as follows: Section 2 discusses hardware for hand pose recognition and recovery estimation. Section 3 examines machine learning and deep learning algorithms used for classification and prediction in hand pose recognition and recovery estimation. Section 4 explores hand pose recognition and recovery estimation within the context of telerehabilitation. Section 5 addresses clinical assessment of recovery levels, and Section 6 presents the discussion and conclusion.

METHODOLOGY

HARDWARE FOR HAND POSE RECOGNITION AND RECOVERY ESTIMATION

The human hand is the primary tool to interact with the external world (Athota & Sumathi, 2022). It is an example of a complex articulate object that exhibits many degrees of freedom (DoF), self-similarities, self-occlusion, and constrained parameters. Hand pose recognition is a technique that involves detecting and recognizing different hand gestures made by individuals. This technology has become increasingly popular in recent years due to its potential applications in areas such as sign language recognition, gesture-based interfaces, and human-robot interaction(W. Chen et al. 2020). Figure 1 depicts the schematic diagram of the processes involved in hand pose recognition.

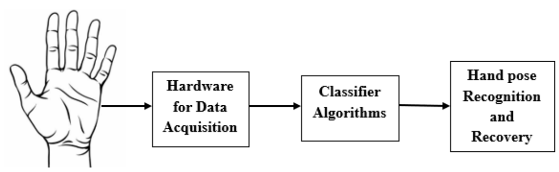

FIGURE 1. Schematic Diagram of Hand pose Recognition and Recovery Estimation

Hand pose recognition involves two main components: the hardware and the software to achieve gesture recognition (X. Chen & Wang, 2013). The hardware component of hand pose recognition is the type of equipment, instruments, or devices used for data collection or image capturing of the human hand when performing tasks or static gestures. There are several approaches deployed by researchers for data collection of hand pose recognition and are grouped into two types of hand pose recognition hardware methods: the computer vision-based method and the wearable sensor method (W. Chen et al. 2020).

COMPUTER VISION-BASED METHOD

The computer vision community has witnessed rapid advancement in recent years. Computer vision is one of the methods used for acquiring data or images for hand pose recognition. Computer vision as the name implies deals with images and computer graphics to analyze and achieve hand pose recognition (W. Chen et al. 2020). Many studies deployed different vision-based sensors such as Red Green Blue (RGB) cameras, RGB-D cameras (Kinect sensors), and Leap motion control sensors to capture the images for hand pose recognition.

RGB cameras are vision-based devices used for capturing hand images to recognize the hand pose. RGB camera utilizes a wavelength of light from 400-700nm, which is the same spectrum that the human eye perceives and captures the images to recognize the hand pose (Tychola et al. 2022). It works by using a sensor to detect incoming light and convert it into a digital signal that can be processed and stored as image data. In contrast to wearable sensors, cameras use indirect measurements by capturing images of the hand and determining the positions of hand joints through sophisticated algorithms.

Many studies proposed RGB cameras for capturing hand images and evaluating the hand pose. For example, Wadhawan & Kumar (2020) and Kwolek et al. (2021) deploy an RGB camera for recognizing the hand gesture used for sign language. Moreover, RGB cameras were proposed by Y. Li & Zhang (2022), and Núñez Fernández & Kwolek (2018) for hand pose recognition and Rastgoo et al. (2018) combined RGB and leap motion control sensor to recognize the hand gesture for sign language. However, RGB cameras require light to operate which predicts the quality and accuracy of the image data.

The advent of readily available depth sensors simplifies hand pose recognition by resolving depth ambiguity, with many of the recently proposed techniques primarily relying on depth maps. The RGB-D cameras provide depth information by emitting a structured light pattern, infrared light, or using time-of-flight measurements to calculate the distance between the camera and objects in the scene. This depth information can be used to create a 3D point cloud of the scene. The RGB-D cameras give a more accurate and detailed model of the scene (W. Chen et al. 2020). Recently, many researchers proposed the RGB-D for hand pose recognition and hand pose estimation which deals with the kinematic model of the hand. Tran et al. (2020), Ma & Peng (2018), and Bakheet & Al-Hamadi (2021) deployed RGB-D camera for hand gesture recognition. Figure 2 depicts the XBOX 360 model Kinect camera.

FIGURE 2. XBOX 360 model RBG-D (Micro Kinect) Camera

The leap motion control sensor as depicted in Figure 3, is a powerful device that can recognize many hand gestures. The leap motion control uses a combination of infrared cameras and optical sensors to track the movement of hands and fingers with high precision and low latency. It can track individual fingers and their movements, as well as recognize hand gestures such as pinching, swiping, and grabbing. The ease of operation and precision characteristics of the camera paved way for the recent increase in sign language recognition. Naglot & Kulkarni, (2016), and Mittal et al. (2019) deploy the camera for hand gesture recognition in sign language.

FIGURE 3. Leap Motion Control Sensor

Computer vision-based methods for hand pose recognition are quite cheap, easy to operate, and comfortable to use as no extra device is worn by the subjects. However, despite the advanced camera specifications found in most smartphones, several challenges persist. These include the restricted field of view of the capturing device, significant computational demands, and the necessity for multiple cameras to ensure reliable results owing to issues related to depth perception and occlusion. These inherent issues undermine the feasibility of the entire system for the advancement of real-time recognition applications.

WEARABLE SENSOR METHOD

The endeavour to create wearable devices for recognizing hand gestures and estimating poses commenced in the 1970s, and the field has sustained its momentum for over four decades (Chen et al. 2020). Wearable biosensors are attracting significant attention for their ability to offer continuous, real-time physiological data through dynamic, non-invasive measurement of parameters.

Wearable sensors are becoming increasingly popular in various applications such as sports and fitness tracking, health monitoring, sleep tracking, fall detection, and more (Kim et al. 2019). In recent years, many studies have deployed different wearable sensors for hand pose recognition. The wearable sensors are directly placed on the subject hand or used on a glove (called a data glove) to collect the hand data. There are typically four main wearable sensors deployed by researchers in hand pose recognition and hand pose recovery estimation. These wearable sensors include an Inertia measuring unit (IMU), Stretch sensor, Electromyography (EMG), and Flex (bending) sensor with Stretch sensor not fully exploited.

Stretch sensors are seeing growing utilization in measuring human body movements due to their capacity to stretch and conform with the shape of the joints and other flexible body parts, enabling the acquisition of high-quality measurements. Advances in material science and sensing technology have led to the introduction of various stretch sensors tailored to different sizes and sensitivities to suit diverse applications, with some also capable of measuring pressure.

Stretch sensors are slender, comfortable, and conform well to the hand, offering exceptional dexterity and sensitivity. These sensors are typically either resistors, with resistivity directly correlating to deformation, or capacitors, with capacitance proportional to deformation. Figure 4 (a) & (b) depict a developed stretchable sensor at electronic system laboratory international Islamic University, Malaysia and the commercial stretch sensors by Leap company respectively. Many recent works have proposed different designs and implementations of the stretch sensor. For example, Rumon et al. (2022) implement 6 stretch sensors to monitor the breath rate of subjects. Jiang et al. (2020) and Glauser et al. (2019) deployed stretch sensors to measure the deformation of the hand when performing hand movement.

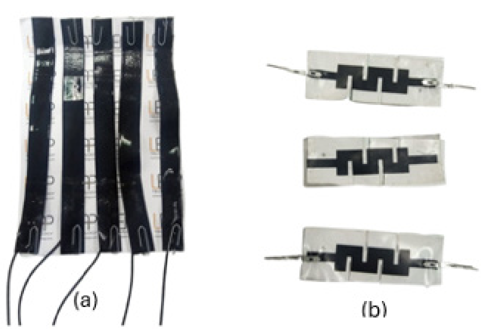

FIGURE 4. Stretchable Sensor (a) Developed Stretch Sensor, (b) Commercial Stretch Sensors

Bend or flex sensors are passive resistive devices commonly employed for measuring deflection angles and are among the most extensively utilized sensors in hand wearables. These sensors are thin and come in various sizes, facilitating easy placement on a glove over knuckles or finger joints. Additionally, they offer advantages such as a relatively long lifespan, affordability, and resilience across a wide range of temperatures, making them a favoured choice for measuring various hand joints (Chen W. et al. 2020). Beyond commercial products, numerous research endeavors aim to design gloves incorporating bend sensors for various practical purposes. Some glove designs utilize off-the-shelf bend sensors as well. Chen et al. used flex sensors on the finger joints fuse with pressure sensors to recognize 16 gestures and 6 tasks of single finger and multiple fingers respectively (Chen et al. 2021). Wei-Chieh et al. designed smart gloves using flex sensors for data collection. The data was used for hand gesture recognition (Chuang et al. 2019). Panda et al. (2021) utilize two flex sensors placed on the index finger and middle finger for hand gesture recognition. Figure 5 depicts the sample of a 2.2-inches flex sensor.

FIGURE 5. 2.2 inches Flex Sensor

IMUs typically comprise accelerometers, gyroscopes, and occasionally magnetometers to deliver measurements of linear accelerations and rotational rates. They are frequently integrated into wearable devices to capture orientation and motion-related characteristics of body parts, including hands and fingers (Chen W. et al. 2020). Studies have demonstrated the ability of IMUs to precisely gauge motor function and offer insights into the distinct motor elements influencing task execution (Hughes et al. 2022). Many studies propose IMU sensors for data collection. Hughes et al. (2022) placed an IMU sensor on the wrist to measure hand movement when conducting three ADL tasks. P. W. Chen et al. (2021) placed five IMU sensors on the wrists, forearms, and abdomen to measure part movement when conducting 19 ADL/IADL tasks. Figure 6 depicts the IMU sensor used in wrist attached.

FIGURE 6. IMU Sensor used in wrist attachment

Hand gesture recognition technology based on surface electromyography (sEMG) as depicted in Figure 7 has been an active research direction due to its broad applications in myoelectric control. Wearable biosensors are attracting considerable attention because of their capacity to offer continuous, real-time physiological data through dynamic, non-invasive monitoring of muscle signals (Kim et al. 2019). Electromyography (EMG), Electrocardiogram (ECG), and Electroencephalogram (EEG) are the biosensors used for measuring the signals of muscle, heart, and brain respectively. EMG signals are used in monitoring the recovery level when conducting training and for measuring the motor function of subjects (Benatti et al. 2015). Zhu et al. (2021); Benatti et al. (2015); Asif et al. (2020); Moin et al. (2021) deployed EMG signal for hand gesture recognition when conducting ADL tasks. Furthermore, Jaramillo et al. used the EMG signals for sign language recognition (Jaramillo-Yánez et al. 2020). Ageishi et al. combines EEG signals with a camera to recognize hand gestures when conducting tasks (Ageishi et al. 2021). However, the EMG signals are being affected by noise which distorts the signal and affects the accuracy of the readings.

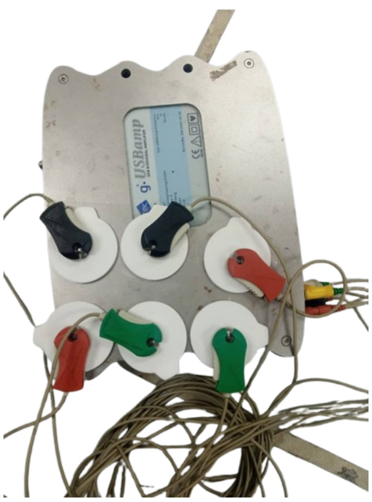

FIGURE 7. Electromyography from G. TECH company

ALGORITHMS FOR HAND POSE RECOGNITION AND RECOVERY ESTIMATION

Hand pose recognition is a field that involves identifying the hand pose or configuration from the sensory data or camera images. Recognition involves the feature extraction and classification of acquired data/images to identify the hand pose/gesture and predict the sign language or gesture-based control or human-robot interaction. There are several algorithms or techniques used for hand pose recognition including Machine learning algorithms, Deep learning algorithms, and Statistical Algorithm.

MACHINE LEARNING ALGORITHMS

In recent years, more and more researchers have used machine learning algorithms to estimate hand poses and classify hand gestures. Machine learning improves the prediction and classification of joint movement and joint angles which improves the general accuracy of the model. Machine learning consists of two stages which are training and testing (Laurent et al. 2022). In the training phase, a collection of input and output data sets is provided to the machine learning algorithm. Different machine learning algorithms have been deployed by several researchers which include k- Nearest Neighbor (k-NN), Decision Tree (DT), and Random Forest (RF).

The K-nearest neighbors (KNN) algorithm, applicable to both classification and regression tasks, operates by identifying the k-nearest data points to a specified data point and leveraging their values to make predictions or estimates. For classification purposes, KNN assigns a class label to a new data point based on the majority class among its k-nearest neighbors. It is simple and easy to understand, making it a popular algorithm for beginners (Zhang Z. et al, 2016). Nogales & Benal Cazar, (2020) deploy KNN classifier with distance matric to classify and recognized five static hand gestures in real-time. Leap motion sensor was utilized for data collection. An accuracy of 92.22% for classification and 77.64% for recognition was achieved within a timeframe of 287 milliseconds. Alksasbeh et al. (2021) developed a smart hand gesture recognition for video annotation purposed. A classroom video was utilized, and 20 hand gestures were extracted. The KNN algorithm extracted the hand parameters eventually recognizing the hand gestures. A mean accuracy rate of 97% was attained. Moreover, Tofighi et al. (2013) utilized K-NN and SVM to evaluate the hand posture recognition on Hand Reader dataset. The Hand Reader dataset comprised 500 images capturing 10 hand postures performed by 50 individuals, both male and female. The images were captured using RGB camera and the K-NN classifier achieved a recognition accuracy of 93% using nearest neighbor k=5.

Decision Trees (DT) is a versatile machine learning algorithm utilized for both classification and regression tasks. DT operates by iteratively partitioning the data according to the values of various features, thus constructing a tree-like model for making predictions. In classification tasks, every node within the tree signifies a test conducted on a specific feature, with the branches denoting the potential outcomes of the test. The terminal nodes, or leaf nodes, of the tree represent the class labels. For the classification of a new data point, the process begins at the root of the tree, proceeding along the branches aligned with the values of the data point's features until reaching a leaf node that signifies the predicted class label. DT offer numerous advantages, including the capability to handle both categorical and numerical data, model nonlinear relationships between features and the target variable, and visualize the decision-making process (Shafiqah et al. 2024). Chen et al. (2021) classify 16 kinds of finger gestures using DT model. an average accuracy of 88.52% for the 6 features extracted was achieved. Moreover, Chang et al. deployed DT for real-time American sign language (ASL) and general gesture recognition. Kinect camera was utilized for data collection (Chang et al. 2013). An accuracy of 94.33% and 95.01 were for ASL and general gesture recognition respectively. Furthermore, Assegie & Nair, (2019) utilized DT to recognize handwritten digits. The standard Kaggle digit dataset was used for recognition. An average classification of 84.73% was achieved for recognizing 0-9. Song et al. proposed gradient bosting decision tree (GBDT) to recognize 12 gestures for human-computer interaction. The proposed algorithm achieved an overall hand gesture recognition accuracy of 91% (Song et al. 2019).

Random Forest (RF) is a machine learning algorithm employed for both classification and regression tasks. RF functions by constructing an ensemble of decision trees, wherein each tree is developed on a random subset of the features and data points. When predicting for a new data point, each decision tree within the ensemble generates its prediction. In classification tasks, the final prediction is determined by the majority vote of the individual trees, while in regression tasks, it is determined by the average of the predictions from the individual trees. RF has several advantages over a single decision tree, such as reduced variance (i.e., improved generalization) and the ability to handle high-dimensional data. It also has several hyperparameters that can be tuned to achieve optimal performance, such as the number of trees in the ensemble and the size of the subsets used to build each tree(Charbuty & Abdulazeez, 2021). P. W. Chen et al. (2021) classify seven ADL tasks using decision tree as classifier. A performance matric accuracy of 79%, precision of 80% and recall of 79% was achieved for the training set and accuracy of 80%, precision of 84% and recall of 80% was obtained. Furthermore, Bargellesi et al. (2019) utilized random forest classifier for hand gesture recognition using wireless wearable motion capture sensor. 12 infrared video cameras were used for data collection. The data were classified into two for the experiment. An accuracy of 97% and 94% were achieved for the first and second dataset respectively. Moreover, Zhao et al. (2012) detected and recognized hand gesture in real-time. Random forest classifier was utilized to classify the hand images and achieved an accuracy rate of 92.23% on the dataset. (Kim B. et al. 2013.) utilized RF and local binary pattern to recognized hand pose. The hand region was localized from the entire image using depth camera. The local binary pattern feature was extracted from the data used for the classification. A recognition accuracy of 94.3% was achieve for recognizing 7 hand poses.

DEEP LEARNING ALGORITHMS

Deep learning methodologies like Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have demonstrated remarkable performance in hand pose recognition. These techniques involve learning features directly from the data or images and utilizing these features to predict the hand pose. Prominent deep learning architectures for hand pose recognition include Residual Networks (ResNet), Visual Geometry Group Networks (VGG), and Long-Short Term Memory (LSTM)(Z. A. Zhu et al. 2019).

ANN, a category of deep learning algorithms, draws inspiration from the structure and functionality of biological neural networks found in the human brain. ANNs consist of interconnected nodes known as artificial neurons, arranged in layers. Typically, input data is introduced to the input layer of the network, while the output of the network is derived from the output layer. The intermediate layers, known as hidden layers, process the input data and extract relevant features for the task at hand. The neurons in each layer of the network are connected to the neurons in the previous and next layers, with each connection having an associated weight. Throughout the training process, these weights undergo adjustments determined by a loss function, which gauges the disparity between the network's predicted output and the actual output for each training instance. The objective of training is to minimize this loss function, typically accomplished through the utilization of an optimization algorithm like stochastic gradient descent to modify the weights. ANNs are used for a wide range of tasks, including classification, regression, and clustering (Ali Malla et al. 2024). They are particularly effective for tasks that involve high-dimensional data, such as images or speech, hand gesture recognition, and pose estimation (Vijayan et al. 2021). Naglot & Kulkarni (2016) classify the 26 American sign language using multi-layer perceptron neural network. Leap motion controller sensor was used to capture the images when performing the signs of the alphabets. A recognition accuracy of 96.15% was achieved. Preethi & Ganapathy (2022) deploy ANN classifier in detecting lung cancer. A total of 1339 samples data was used with 75% training data and 25% testing data. An accuracy of 97.95%, Recall of 98.55%, specification of 96.55% and precision of 98.55% was achieved.

Initially crafted to associate image data with a solitary output variable, typically for classification tasks, Convolutional Neural Networks (CNN) excel at learning from raw image data by leveraging on correlations between neighbouring pixels. Their effectiveness is particularly notable when dealing with data possessing spatial relationships, rendering CNNs well-suited for predicting human motion in time-series data (Johari et al. 2023). Asif et al. (2020) deployed CNN for recognizing 10 hand poses using EMG sensor data. The CNN classifier achieved 92% recognition accuracy. Moreover, Glauser et al. (2019) used 44 stretch sensors to design a glove for hand pose estimation using a CNN classifier and a deviation of 5.8º was achieved. Furthermore, Rastgoo et al. (2018) considered the hand gesture data from RGBD sensor to classify and recognition the American sign language finger spelling using CNN as the classifier. The proposed CNN classifier was used on different data sources which achieved 90% accuracy with NYU data, 99.31% with Massey university data, 98.13% for ASL fingerspelling data. Wadhawan & Kumar, (2020) deployed CNN for Indian sign language recognition. The colored and grayscale images from RGB camera were used to obtain an accuracy of 99.72% and 99.90% respectively. Moreover, Abdulhussein & Raheem, (2020) used CNN to classify the 24 alphabets static characters of ASL. The classification accuracy of 99.3% and error of loss function of 0.0002 was achieved.

RNN was designed for sequence prediction problems. Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), capitalizes on temporal dependencies within data, accounting for their effectiveness in natural language processing. Consequently, they prove advantageous for tasks requiring the prediction of motion sequences. The fundamental objective of RNNs is to minimize the loss function through backpropagation to adapt parameters. Regrettably, training LSTM networks demands significant computational resources and relies on extensive datasets, which are seldom accessible in the field of biomechanics (Li R. et al. 2024). Kwolek et al. (2021) uses RGB camera images to recognize Japanese sign language. ResNet, VCC, and Generative Adversarial Networks (GANs) were used for the classification, and an accuracy of 90% was achieved. Moreover, Ali et al. (2020) considered big cloud data from health monitoring framework using wearable sensors and social networking data. A bidirectional long short-term memory (Bi-LSTM) was proposed to classify the data into healthcare monitoring and recommendations. The classification achieved an accuracy of 90%, precision of 88%, Recall of 90%, and F1 score of 89%. Mittal et al. (2019) deploy LSTM for continuous sign language recognition using leap motion sensor data. An accuracy of 72.3% and 89.5% was achieved for signed sentence and isolated sign words recognition respectively.

STATISTICAL ALGORITHMS

Statistical algorithms are another popular approach to hand pose recognition. They use statistical models to represent the hand pose and estimate the pose parameters from the input data. Examples of statistical methods include Support Vector Machine (SVM), Linear Discrimination Algorithm (LDA), Hidden Markov Models (HMMs), and Gaussian Mixture Models (GMMs).

Support Vector Machines (SVMs) are statistical machine-learning algorithms applicable to both classification and regression tasks. SVMs operate by identifying the optimal boundary, known as a “hyperplane,” between two classes within a dataset. This hyperplane is chosen to maximize the margin, which represents the distance between the hyperplane and the closest data points of each class. SVMs excel, especially in scenarios involving high-dimensional data, where other classification algorithms may encounter difficulties. Additionally, SVMs can accommodate various kernel functions, such as linear, polynomial, and radial basis functions, to capture nonlinear relationships between variables. SVMs offer several advantages, including their capability to handle both linear and nonlinear classification problems, their effectiveness with high-dimensional data, and their robustness in managing noisy datasets (Huu & Phung Ngoc, 2021). Many studies proposed SVM for data/image classification. Zhu et al. (2021) deployed SVM and LDA for the classification of EMG signals and achieved an accuracy above 85%. Moreover, Kalaiyarasi et al. (2020) achieved a classification accuracy of 96.49%, precision of 98.30% and recall of 92.06% using SVM algorithm to classify the benign or malignant tumor in cancer detection. In addition, Chen et al. (2021) classify seven ADL tasks using SVM model and achieved a training accuracy of 97%, precision of 97% and recall of 97% and a testing set accuracy of 90%, precision of 92% and recall of 90%.

Linear Discriminant Analysis (LDA) is a statistical machine learning algorithm widely employed in classification tasks. LDA functions by identifying a linear combination of features that effectively separates the classes within the dataset. Specifically, LDA aims to discover a projection of the data that optimizes the ratio of between-class variance to within-class variance. This entails maximizing the distance between class means while minimizing variation within each class. Once the optimal projection is determined, it can be utilized to classify new data points by assigning them to the class with the nearest mean in the projected space. LDA is favoured for its simplicity, efficiency, and suitability for application with small datasets (Saeed et al. 2021). Kopke et al. (2018) used two LDA classifiers to control shoulder abduction and adduction as well as external and internal rotation simultaneously. The classifiers used force, moment, and EMG signals as datasets. An accuracy of 95.4%, 92.6%, and 97.3% were obtained for the respective datasets. In addition, Saeed et al. (2021) utilized LDA classifier to classify 52 and 11 hand movements from two different datasets. The algorithm achieved a classification accuracy of 85.41% and 93.54% for the 52 and 11 movements respectively. Furthermore, Atangana et al. (2020) deployed LDA for feature selection and dimensionality reducing of the EEG signal. MLP neural network was used for the classification of the signal. A sensitivity, specificity, and accuracy of 100% were achieved.

Hidden Markov Models (HMMs) are statistical machine learning algorithms widely employed for analyzing time series data. HMMs belong to the category of generative models, which aim to represent the underlying state of a system that is not directly observable but can only be inferred from observable data. In an HMM, the system is depicted as a Markov process, where the states of the system evolve over time according to a transition probability matrix. However, these states are not directly observable; instead, they emit observable symbols (such as words, images, or sensor measurements) with probabilities contingent on the current state. When provided with a sequence of observable symbols, HMMs can deduce the most probable sequence of hidden states responsible for generating those symbols. This inference is typically accomplished using algorithms like the Forward-Backward algorithm or the Viterbi algorithm, which compute the likelihood of the observed sequence under various state sequences. HMM has several advantages, such as the ability to model temporal dependencies in the data and the ability to handle missing or noisy data (Vijayan et al. 2021). Roth et al. (2021) utilize HMM to segment and classify the free-living gait of 28 Parkinson's disease patients. The HMM achieved a mean F1-score of 92.1%.

Gaussian Mixture Model (GMM) is a statistical machine learning algorithm utilized for clustering and density estimation tasks. GMM operates as a probabilistic model, representing intricate distributions through a blend of simpler Gaussian distributions. Within GMM, each observation is hypothesized to originate from one of K Gaussian distributions, where K, a hyperparameter, dictates the number of components within the mixture. Each Gaussian distribution is delineated by its mean and covariance matrix, derived from the data through the Expectation-Maximization (EM) algorithm. GMM can be applied for clustering by assigning each observation to the component exhibiting the highest probability or for density estimation by assessing the probability density function of the mixture at a given point. GMM offers numerous advantages, including its capability to capture complex distributions beyond the scope of a single Gaussian distribution and its adeptness at handling high-dimensional data (Jinxing et al. 2017)

. The proposed algorithm was tested on three different datasets and achieved an average accuracy of 95.77%. Moreover, Wan et al. (2019) proposed separability criterion GMM to improve the classification accuracy of the models. Ten datasets were used to validate the proposed SC-GMM model. The proposed model achieved an average accuracy of 85.25% compared to the original GMM accuracy average of 82.79%. Furthermore, Prabakaran et al. (2019) deployed GMM for cancer classification. Three datasets were used for the classification and obtained an average classification of 93%. T. Zhang et al. (2020) utilize fuzzy gaussian model to classify 8 gestures. The model achieved 98.06% accuracy.

HAND RECOVERY ESTIMATION FOR TELEREHABILITATION

Assessing and monitoring a patient's movement quality and utilization of their affected limb during daily activities (ADLs) provide crucial insights into the recovery trajectory and potential long-term impairments. Presently, therapists evaluate ADL performance using diverse methods, including clinical observation, self-reported logs/questionnaires, and clinical performance assessments (Azri et al. 2024). To effectively guide telerehabilitation therapy, medical professionals require regularly updated and patient-specific information regarding the progress of recovery. Assessment of the recovery level information of the patient is significant to the therapist's analysis, and the progressive tasks to be assigned to the patient(van Meulen et al. 2015). Traditionally, therapists deploy clinical assessments such as FMA, WMFT, ARAT, and MAL to assess the recovery level of the patient. However, the clinical assessments are mostly retrospective and susceptible to reporting bias and error. Many studies deploy several techniques to quantify the recovery remotely and correlate the results with the clinical assessment scores. Oubre et al. (2020) deployed 2 IMU sensors placed on the wrist and the sternum for data collection when performing ADL tasks. The unsupervised clustering algorithm and the supervised regression model were employed to predict the Fugl-Meyer Assessment (FMA) score using features extracted from the sub-movement. 23 stroke survivors validated the model and achieved a Root Means Square Error (RMSE) of 18.2%. Chaeibakhsh et al. (2016) deployed 5 IMU and single IMU sensors respectively are used to measure the upper extremity movements of a stroke survivor, and the results were correlated with FMA upper extremity traditional assessment scale. Pan et al. (2021) deployed IMU and EMG sensors to estimate the recovery of the patient. Five features were extracted from both sensor data by the non-negative matrix factorization algorithm. The results were correlated with the FMA score which shows a significate correlation. Yassin et al. (2021) utilized electromyography (EMG) signals as a biofeedback tool, enabling physiotherapists to precisely develop and remotely monitor personalized treatment for each patient. The setup consists of EMG sensor for acquiring the muscle activity data, two cell phones for the patient and therapist. The monitoring and control were achieved via Google Firebase database. The system was evaluated by comparing the proposed system RMSE and BIOPAC system RMSE. Furthermore, Anton et al. (2018) deployed Kinect camera for virtual therapy. The system selects, evaluates, and remotely manages therapeutic exercises remotely. The selected exercise by the therapist was performed by the patient under the monitoring of the Kinect camera for real time feedback and evaluation of the activity by the therapist. Moreover, Roberts & Gao, (2018) proposed a mobile platform that uses RGB camera, machine learning algorithm, and statistical analysis to track and monitor the range of motion during therapeutic exercise remotely. The system known as PyTracker was evaluated and proven to deliver clinical accuracy. The system uses a classifier built from Haar Cascades to identify the features. The result of PyTracker was compared with Goniometer reading and an average difference of 2.5 (degree) for four parts movement was obtained. In addition, Sabatelli et al. (2022) considered remote monitoring of people with Parkinson's disease while performing rehabilitation sessions at their homes. A commercial smartwatch was used for data collection and statistical analysis (ANOVA) was used for finding significant changes in physiological variables throughout the rehabilitation therapy. The ANOVA P-values for the daily and sleep activities were evaluated. Radmanesh et al. (2021). proposed a control of a wrist telerehabilitation system based on recovery indices and reproduction of the periodic tasks The dynamic of the master and slave arrangement was deployed with robot being controlled by the therapist. GMM and GMR models were employed to capture the therapist's motions from demonstrations, subsequently reproducing the task with high precision and consistency. The patient follows the end effector of the slave robot. The motion was classified based on the recovery levels. The naïve bayes, DT, SVM, and KNN obtained an accuracy of 92.5%, 96.67%, 96.67%, and 97.5% respectively.

CLINICAL ASSESSMENT FOR UPPER LIMB RECOVERY ESTIMATION

Clinical assessment of a stroke patient is a critical step in determining the appropriate treatment and management of the patient's condition. The clinical assessment also helps to determine the severity of the stroke which can affect the patient's prognosis and the type of care that is needed. Clinical assessments for stroke patients in performing ADLs involve evaluating the patient's ability to perform essential daily tasks such as bathing, dressing, eating, and using the toilet etc. This is critical for identifying areas of impairment and developing a tailored rehabilitation program to improve functional abilities and quality of life (Azri et al. 2024). The clinical assessment can be divided into four types (Pan et al. 2021):

1. Observation
2. Performance-based assessment
3. Objective measurement
4. Self-reported Questionnaire (HAQ)

Observation assessment is the type of assessment that involves watching the patient perform different ADL tasks to evaluate their motion function. The therapist can observe the patient's movement pattern, range of motion, coordination, and balance while they perform activities such as dressing, bathing, grooming, eating, and other daily activities.

Performance-based assessments are the type of assessment that involves having the patient perform standardized tasks that simulate daily activities. The assessment can be used to evaluate a patient's motor function in ADL and provide information about their level of independence and ability to perform daily tasks (Li et al. 2022). Examples of such assessments are the Functional Independence Measure (FIM), Motor Activity Log (MAL), Activity Research Arm Test (ARAT), Wolf Motor Function Test (WMFT), and Barthel index among others.

Objective measurement assesses specific aspects of the motor function such as strength, endurance, and range of motion. Examples of objective measurements are the grip strength test, the time up and go (TUG) test, and the 6-minute walk test. At present, therapists assess upper limb activities of daily living (ADL) performance using various measures, including FIM, MAL, WMFT, ARAT, and the Barthel Index, among others. Each assessment has certain tasks that the patient conducts which are attached to a scoring that the therapist used to categorize the recovery level of the patient (Li et al. 2022) .

The clinical assessment FMA (Fugl-Meyer Assessment) is a widely used and standardized measure of motor function in individuals who have suffered a stroke or other neurological conditions affecting their motor abilities. The FMA evaluates an individual's motor recovery by assessing their ability to perform specific movements and tasks, such as reaching, grasping, and walking. The assessment is divided into several sections that evaluate different aspects of motor function, including upper extremity, lower extremity, and balance. The FMA is scored on a scale from 0 to 100, with higher scores indicating better motor function (Li et al. 2022). The assessment is typically administered by a trained healthcare professional, such as a physical therapist or occupational therapist, and takes approximately 45-60 minutes to complete. Van Meulen et al. (2015) and Chaeibakhsh et al. (2016) deployed 17 IMU and 5 IMU sensors respectively are used to measure the upper extremity movements of a stroke survivor and the results were correlated with FMA upper extremity traditional assessment scale. Pan et al. (2021) used IMU sensor data and EMG signals were collected from the upper limb during voluntary upward reaching. The assessment of the recovery level was correlated with the FMA assessment scale.

The clinical assessment WMFT (Wolf Motor Function Test) is a standardized measure of upper extremity motor function in individuals who have suffered a stroke or other neurological conditions affecting their motor abilities. The WMFT evaluates an individual's ability to perform specific upper extremity tasks, such as reaching, grasping, and manipulating objects. The assessment includes timed and functional tasks, such as pouring water from a pitcher or folding towels, as well as strength and range of motion measurements. The WMFT is scored based on the time taken to complete each task, with longer times indicating poorer motor function. The assessment is typically administered by a trained healthcare professional, such as a physical therapist or occupational therapist, and takes approximately 60-90 minutes to complete (Li H.T. et al. 2015). The WMFT is considered a reliable and valid measure of upper extremity motor function and is often used in research studies and clinical practice to assess motor recovery and track progress over time. It can be used to identify specific areas of motor function that need to be addressed in rehabilitation and to evaluate the effectiveness of various interventions. Li H.T et al. 2015) deployed IMU signals of the upper limb during tasks to assess the recovery level and correlate the proposed quantitative evaluation indices with the WMFT traditional rehabilitation assessment scale.

The ARAT (Action Research Arm Test) is a clinical assessment that measures upper extremity function in individuals who have suffered a stroke or other neurological conditions affecting their motor abilities. The ARAT assesses an individual's ability to perform 19 different functional tasks, such as grasping, gripping, and lifting objects of varying sizes and shapes. The assessment is typically administered by a trained healthcare professional, such as a physical therapist or occupational therapist, and takes approximately 15-20 minutes to complete. The ARAT is scored on a 4-point ordinal scale, with higher scores indicating better upper extremity function. The assessment is used to evaluate motor recovery, track progress over time, and identify specific areas of motor function that need to be addressed in rehabilitation (Murphy et al. 2021). It is particularly useful for assessing functional improvements in the affected upper extremity following a stroke or other neurological conditions.

The MAL (Motor Activity Log) is a clinical assessment that measures an individual's self-reported use of their affected upper extremity in daily activities after a stroke or other neurological conditions affecting their motor abilities. The MAL assesses an individual's perceived amount and quality of use of their affected arm and hand during specific daily activities, such as reaching, grasping, and manipulating objects (Azri et al. 2024). The assessment is typically administered by a trained healthcare professional, such as a physical therapist or occupational therapist, and takes approximately 20-30 minutes to complete. The MAL is scored on a 5-point ordinal scale, with higher scores indicating greater use and quality of movement of the affected arm and hand. The assessment is used to evaluate motor recovery, track progress over time, and identify specific areas of motor function that need to be addressed in rehabilitation. It is particularly useful for assessing an individual's perceived functional improvements in their affected upper extremity following a stroke or other neurological conditions.

The Barthel Index is a clinical assessment tool used to measure an individual's level of functional independence in activities of daily living (ADLs). It is commonly used in individuals who have suffered a stroke or other neurological conditions affecting their ability to perform ADLs. The Barthel Index assesses an individual's ability to perform 10 basic ADLs, including feeding, grooming, transferring, walking, and bathing. The assessment is typically administered by a trained healthcare professional, such as a physical therapist or occupational therapist, and takes approximately 10-15 minutes to complete. The Barthel Index is scored on a scale from 0 to 100, with higher scores indicating greater independence in ADLs. The assessment is used to evaluate an individual's level of functional independence and track changes over time, as well as to identify specific areas of functional deficit that may require intervention. It is particularly useful for assessing changes in functional independence following treatment interventions and can be used to guide rehabilitation and discharge planning (dos Santos Barros et al. 2022).

The improvement of patients' motor function heavily relies on rehabilitation training. However, considering the individual variances among patients, it is crucial to tailor personalized rehabilitation programs based on their distinct levels of motor impairment. Currently, medical assessment scale methods are commonly employed in clinics to evaluate the motor functions of stroke patients. While these scales demonstrate good reliability and validity, they possess a limitation in their sensitivity to capture the nuances of sensorimotor performance due to their use of ordinal scales.

DISCUSSION

This study reviews various hand pose recognition hardware, hand poses recognition algorithms, clinical assessment, and hand pose recognition for telerehabilitation. Computer vision-based and wearable sensors are the two-hardware utilized in hand pose recognition. The vision-based sensors comprise:

1. RGB camera.
2. RGB-D camera.
3. leap motion control sensors.
4. Infrared camera.

Using a camera offers the primary advantage of eliminating the necessity for wearing sensors and reducing system building costs. Cameras are generally inexpensive, and many laptops incorporate high-specification cameras to address issues like blurriness common with web cameras. However, despite the prevalence of high-quality cameras in smartphones, there are several challenges. These include the limited field of view, high computational demands, and the requirement for multiple cameras to ensure robust outcomes due to depth and occlusion issues. These inherent limitations render the system impractical for real-time recognition applications. Additionally, camera-based gesture detection systems are sensitive to lighting conditions and demand substantial processing resources. The wearable sensors deployed by researchers include:

1. Inertial measurement unit (IMU)
2. Electromyograph signals (EMG)
3. Flex (bending) sensor.
4. Stretchable sensor
5. Electroencephalography signals (EEG).

One significant benefit of wearable sensor systems compared to vision-based systems is that sensors can directly transmit essential data, such as bend degree or pitch, to the computing device in voltage values. This eliminates the necessity to convert raw data into meaningful values during processing.

Many researchers deployed different algorithms in recognizing hand poses and estimating the recovery level of patient. The algorithms are grouped into three categories as stated earlier. This includes the machine learning algorithms which comprise of the following:

1. k-Nearest Neighbor (k-NN)
2. Decision Tree (DT)
3. Random Forest (RT)

Then the deep learning algorithm which includes:

1. Artificial Neural Network (ANN)
2. Convolution Neural Network (CNN)
3. Recurrence Neural Network (RNN)

Finally, the statistical machine learning algorithms that include:

1. Support Vector Machine (SVM)
2. Linear Discrimination Algorithm (LDA)
3. Hidden Markov Model (HMM)
4. Gaussian Mixture Model (GMM)

Many studies investigate the hand pose and gesture recognition for human-computer interaction, sign language recognition, ADL tasks recognition, or virtual reality. The algorithm deployed depends on the data acquisition device. The review revealed that computer vision devices produce larger training data in which deep learning algorithms like CNN achieved higher classification accuracy. Furthermore, deep learning algorithms obtained good classification accuracy when used on larger data. However, the accuracy tends to decrease on real-time operation as the computational time is larger. The machine learning algorithm and statistical analysis were utilized when using wearable sensors for data acquisition. The SVM and the KNN algorithm were utilized by many investigators as they achieved good classifications performance matrices. However, two of the most deployed algorithms (SVM, and KNN) performed better on less data and the classification accuracy decreases with increase in the data. This will limit the number of tasks recognized.

Other researchers studied the recovering level and monitoring the motion of the patient when performing rehabilitation exercises. The IMU sensor was deployed by many investigators to acquire the upper-limb data when performing ADL tasks remotely to estimate the recovery level of the patient based on the clinical assessment. The ANOVA was used to correlate the acquired data with the scoring of the clinical assessment used. However, wearing the IMU sensors affect the movement of the upper limb especially the hand and the finger with their dexterous movement during performing ADL tasks. This affects the therapist's evaluation of the recovery level of the patient.

The clinical assessment had been the tool used by professional therapists to evaluate the recovery level of a stroke survivor. The clinical assessments were categorized into observational based, performance bases, objective measurement based, and self-reported questionnaire based as listed below:

1. Observational based
   a. Fug-Meyer Assessment (FMA)
   b. Wolf Motor Function Test (WMFT)
   c. Motor Assessment Scale (MAS)
   d. Upper Extremity Fug-Meyer Assessment (UE-FMA)
2. Performance Based
   a. Activity Research Arm Test (ARAT)
   b. Wolf Motor Function Test (WMFT)
   c. Moto Activity Log (MAL)
   d. Barthel Index
   e. Box and Block Test (BBT)
3. Objective Measurement Base
   a. Fug-Meyer Assessment (FMA)
   b. Activity Research Arm Test (ARAT)
   c. Nine Hole Peg Test (NHPT)
   d. Wolf Motor Function Test (WMFT)
4. Self-report Questionnaire
   a. Stroke Impact Scale (SIS)
   b. Disabilities of the Arm, Shoulder, and Hand (DASH)
   c. Quick DASH
   d. Modified Ashworth Scale.

Clinical assessment helps the therapist to monitor and schedule therapeutic exercises for the patients. While medical scales demonstrate good reliability and validity, their reliance on subjective scores from physicians poses challenges in reflecting minor functional changes due to coarse evaluation. Consequently, some poststroke patients may exhibit similar evaluation scores despite variations in movement performances. An inherent drawback of these assessments is their limited sensitivity to capture the quality of sensorimotor performance, attributed to the use of ordinal scales. Therefore, the development of a quantitative evaluation method tailored to the specific motion of poststroke patients would be beneficial. Such a method could unveil patients' deficits and offer guidance for the rehabilitation process.

Table 1 provides the summary of the studies that have deployed wearable sensors to recognize the ADL tasks conducted by patients. This will significantly improve the evaluation of the telerehabilitation system. Other researchers considered the estimation of the recovery level and correlated it with the standard clinical assessment scales. Tremendous results were achieved which are more precise and accurate than the clinical scoring by therapist. However, the system will be more robust if the hand pose recognition and hand pose estimation are modeled as a single system.

TABLE 1. Summary of Hand Pose and Recovery Estimation

Author	Year	Hardware	Algorithm	Application	Advantage
Orlov et al.	2019	IMU sensor	SVM	Telerehabilitation	Good robustness.
Chen et al.	2022	IMU sensors	DT, RF, SVM and XGBoost	Telerehabilitation	High precision in real-time.
Abbaspour et al.	2020	EMG sensor	LDA/KNN/MLE/SVM	Telerehabilitation	Several gesture recognitions.
Hughes et al.	2019	IMU/Vicon Camera	Statistical analysis	Telerehabilitation	The system is reliable.
Chen et al.	2020	MYO	KNN/SVM	Telerehabilitation	Many gestures recognition.
Kwolek et al.	2022	RGB camera	CNN	Japan Sign Language	The system is cheap.
Chaeibakhsh et al.	2016	IMU sensors	DT/ Bagging Forest	Motion quality Estimation	Many gestures monitoring.
Yassin et al.	2021	EMG sensor	ANOVA	Telerehabilitation/ Assessment	Linear output
Antoin et al.	2018	Kinect camera	VR/Physiotherapist	Telerehabilitation/ Assessment	The system is cheap and easy to use
Robert et al.	2018	RGB camera	Haar Cascades/ANOVA	Telerehabilitation/ Assessment	Non-invasive.
Sabatelli et al.	2022	Smartwatch	ANOVA	Telerehabilitation / Clinical assessment	The system gives real-time evaluation.
Radmanesh	2021	GMM/GMR	DT/SVM/KNN	Telerehabilitation/ Monitoring	The system evaluates the tasks for irregularities.
Shen et al.	2021	IMU/EMG sensor	ANOVA	Clinical assessment	High precision in gesture recognition
Li et al.	2015	IMU sensor	ANOVA	Clinical Assessment	The system is very sensitive
Denni Nunez-Ferna	2019	RGB camera	Haar Cascade/CNN	Telerehabilitation	Generate more data for deep learning training.
Glauser et al.	2019	Stretch sensor	CNN	Human-computer interaction	High precision in gesture recognition
Jiang et al.	2020	Stretch sensor/ camera	LDA	American Sign language	Low computational load
Tran et al.,	2020	RGB-D camera	CNN	Human-computer interaction	Comfortable for the user as he does not need to wear any sensors.
Ageishi et al.	2021	EEG sensor	CNN	American sign language	High sensitivity

continue ...

... *cont.*

Asif et al.	2020	EMG sensor	CNN	Gesture recognition	More gesture recognition
Bakheet et al.	2021	Kinect camera	SVM	Gesture recognition	Comfortable without wearing extra device
Wadhawan et al.	2020	RGB camera	CNN	Sign language	Comfortable without wearing extra device
Naglot et al.	2022	Leap motion sensor	ANOVA	Sign language	The system is cheap and easy to use
Mitta et al.	2019	Leap motion sensor	LSTM	Sign language	No need for wearing sensors.
Meullen et al.	2015	IMU sensors	ANOVA	Clinical Assessment	Subjectively assess the patient recovery

CONCLUSION

This review examined different techniques for hand pose recognition and recovery of post-stroke patients when performing ADL tasks. The data acquisition devices were discussed, and the advantages and the setbacks of the devices were reviewed with computer vision devices serving as non-invasive and easy to operate. However, the inherited issue of light and occlusion are draw backs of the performance of the device. Various wearable devices were used for hand pose recognition, clinical assessment, and automated monitoring of ADL tasks. The review depicted many wearable devices, and the algorithm deployed for classification and clinical assessment for evaluating the recovery level of the patient. Wearable sensor systems transmit pertinent data, such as bend degree or pitch, directly to the computing device in terms of voltage values. This bypasses the requirement to convert raw data into meaningful values during processing. Moreover, the portable and mobile nature of wearable sensors enables real-time and continuous monitoring of various movements. However, wearing the sensor feels uncomfortable and leads to suboptimal results.

The review depicted that the studies either investigate the hand pose recognition or the recovery estimation of the patient based on the clinical assessment techniques. Automatic hand pose and recovery recognition system with new algorithm that classify both the pose and the recovery of the patient when conducting ADL tasks. This will impel the therapist to objectively evaluate the recovery of the patient. Future work involves wearable stretch sensors placed on the hand for data collection when performing ADL tasks and developing a multi-task model that will recognize the task and the recovery level of the patient.

ACKNOWLEDGEMENT

This research is fully supported by AOARD grant, FA2386-21-1-4026. The authors fully acknowledged Asian Office Aerospace Research Development for the support.

DECLARATION OF COMPETING INTEREST

None.

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