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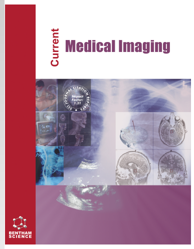

REVIEW ARTICLE

Review for Optimal Human-gesture Design Methodology and Motion Representation of Medical Images using Segmentation from Depth Data and Gesture Recognition

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Abstract:

Human gesture recognition and motion representation have become a vital base of current intelligent human-machine interfaces because of ubiquitous and more comfortable interaction. Human-gesture recognition chiefly deals with recognizing meaningful, expressive body movements involving physical motions of the face, head, arms, fingers, hands, or body. This review article presents a concise overview of optimal human gesture and motion representation of medical images. It surveys various works undertaken on human gesture design and discusses various design methodologies used for image segmentation and gesture recognition. It further provides a general idea of modeling techniques for analyzing hand gesture images and even discusses the diverse techniques involved in motion recognition. This survey provides insight into various efforts and developments made in the gesture/motion recognition domain by analyzing and reviewing the procedures and approaches employed for identifying diverse human motions and gestures for supporting better and devising improved applications in the near future.

Keywords: Human gesture, Hand gesture, Motion recognition, Image segmentation, Gesture recognition, Machine vision.

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1. INTRODUCTION

In the current era of intelligent computing and interactive activity, effective human-machine interaction is gaining the utmost significance in everyday life. In this vein, gesture recognition and motion representation are gaining vast interest. Gesture recognition is the procedure through which gestures performed by the user are identified or recognized by the receiver [1]. Gestures are meaningful, expressive body movements involving physical motions of the face, head, arms, fingers, and hands or the entire body with the motive of interacting with a realistic environment or communicating meaningful information. Gestures constitute an interesting tiny subspace of probable human motion [2]. They can be dynamic (stroke, post-stroke and pre-stroke phases) or static (wherein the user assumes a certain configuration or pose). Certain gestures possess both dynamic and static components (*e.g.* in sign languages). They can even be perceived *via* environment for the data to be communicated elsewhere and consequently rebuilt by the receiver. Human-gesture recognition contains widespread applications, a few of which include developing hearing aids, devising methods for forensic activities, identifying sign language, lie detection, clinically monitoring patients' stress levels or emotional states, navigating in virtual environments, tele-teaching assistance/distance learning, monitoring vehicle drivers' drowsiness levels/ alertness, *etc*. Several procedures have been presented by researchers for handling gesture recognition [3], extending from mathematical modeling depending on hidden Markov sequences [4] to approaches or tools depending on intelligent or soft computing [5]. Typically, along with theoretical concepts, practical gesture recognition implementation requires the exploitation of distinct imaging and monitoring/tracking gadgets like marker-dependent optical tracking, bodysuits, and instrumented gloves. Classical two-dimensional keyboard-, mouse-, and pen-oriented graphical interfaces are usually unfit for operating in virtual conditions. Instead, gadgets that sense human body orientation and position, the direction of sound, speech and gaze, skin response, facial expression, and several other actions of the human state are supportive for modeling communication between the interacting environment and a human. The HG

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recognition/ motion recognition mechanism depending on machine vision is portrayed in Fig. (**1**).

Recently, advanced sensing technologies have emerged for dealing with gesture/motion identification. New types of imaging sensors like Asus Xtion or Microsoft Kinect versions have emerged [6, 7] and unconventional infrared cameras [8] have enabled the acquisition of depth data from imaging sensors. Also, developments in image processing technologies have made desired image segmentation (IS) simpler. In the entire motion/HG recognition procedure, IS is an imperative phase. Several popular IS methods have been proposed by researchers for satisfying distinct IS demands. In the graph cut approach [9], the main concept was to split one image into 'background' and 'object'. It employs a grayscale histogram for describing gray scale distribution and then divides the image into background and object by drawing a cut. It further applies the min-cut/max flow technique for minimizing the energy function of a cut and accomplishes IS through this minimized cut. In these methods, not just a complete image but even every morphological detail is considered. Other IS methods [10 - 12] performed better IS than the graph cut technique. In the HG recognition/ motion recognition mechanism, IS is followed by a feature extraction procedure, wherein imperative features are extracted *via* distinct feature extraction techniques [13 - 15]. After the extortion of required image features, classification is done *via* appropriate classification methods for desired motion/HG recognition.

The different methodologies exploited for HG recognition and motion recognition in Sections 2, 3, 4, 5, and 6 are represented in Fig. (**2**). The techniques employed in existing works for human gesture recognition tasks are mainly categorized into vision-based approaches, sensor-based approaches, artificial intelligence (AI) approaches, and others. The AI approaches are further grouped into Machine Learning (ML) and Deep Learning (DL) techniques. The ML techniques include Support Vector Machines (SVM), Decision Tree (DT), Artificial Neural Networks (ANNs), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Gaussian Mixture Model (GMM), Random Forest (RF), K-Nearest Neighbor (KNN), *etc*. and DL techniques include Deep Neural Networks (DNNs), Long Short Term Memory (LSTM), Generative Adversarial Networks (GAN), Recurrent Neural Networks (RNNs), Multi-layer Feedforward Neural Networks (MFNNs), Residual Networks (ResNets), Convolutional Neural Networks (CNNs), and other Neural Networks (NNs). The other approach category includes appearance-based, model-based, imaging techniques, Hidden Markov Model (HMM), Multilevel Temporal Sampling (MTS), Weighted Depth Movement Map (WDMM), *etc*. These approaches are reviewed in the following sections of the paper.

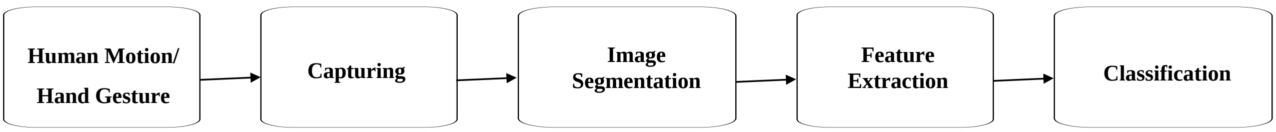

Fig. (1). Motion/HG recognition procedure.

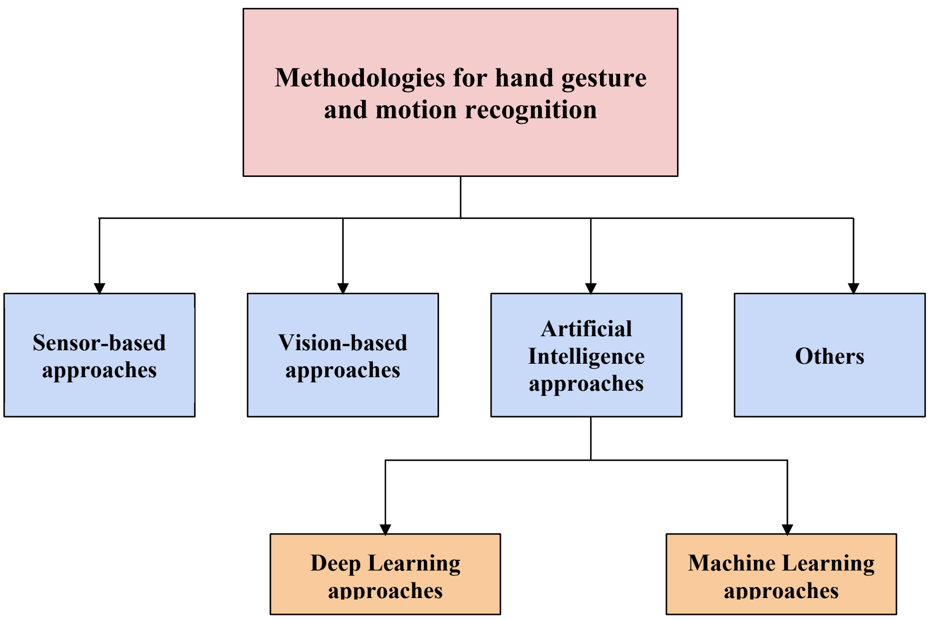

Fig. (2). Overview of human gesture recognition methodologies.

2. RELATED WORKS

For gesture recognition, researchers have employed diverse recognition procedures and techniques in existing research works [16 - 23]. In some studies, vision-based approaches [24 - 26] are exploited while in others sensor-based approaches [27 - 30] are used. However, the core aspect of all these studies is to accomplish precise human gesture recognition. In this section, diverse methods exploited for human gesture identification are presented.

In a study [31], gesture recognition was achieved through a multidimensional attribute learning method. The top-range gesture representations were learned using convolutional residual networks (CResNets) and convolutional long short-term memory networks (CLSTMs). The depth sequences *via* ResNets and spatiotemporal attributes from RGB were learned simultaneously for capturing temporal correlations between them. Moreover, a technique for alleviating variations and disturbances from the background was proposed for attaining good recognition accuracy. Furthermore, gesture-irrelevant attributes were filtered and discriminant movement patterns were captured from RGBD signs. The recognition outputs of individual elements were blended through a straightforward linear fusion method as per the contribution of every element to the ultimate classification. The approach illustrated that integrating several methods of encoding temporal and spatial data resulted in stable and robust spatiotemporal attribute learning with good generalization capability. In another study [32], real-time HG identification was implemented through DL methods and electromyographic (EMG) signals. The EMG signals from the forearm were obtained *via* the Myo armband sensor, followed by feature extraction through autoencoder and HG image classification through artificial feed-forward (AFF) neural network (NN). This approach effectively recognized different HGs like fingers spread, double tap, wave left, fist and wave right with good recognition accuracy. Moreover, in another study [33], HG recognition methodologies based on ANNs were studied. All the chosen methods employed either data glove or digitized camera outcomes as input. Preprocessing on the input image was accomplished through edge detection filtering, thresholding, or normalization for segmenting HG from the background. Feature extraction was executed *via* non-geometric or geometric features and neural networks were applied for HG detection. Deep dynamic NN (DDNN) was proposed for segmenting and recognizing multimodal gestures [34]. It employed a semi-supervised framework depending on the HMM for concurrent gesture image segmentation and recognition of multimodal information containing skeletal features, depth data, and RGB images. The top-level spatiotemporal features were learned using deep NNs. HG recognition was executed using NNs and computer vision [35]. Gaussian mixture-dependent foreground/background segmentation was done for background subtraction and median filtering was applied for discarding noise/irrelevant information from the captured picture. Furthermore, binary thresholding integrated with Otsu's method was implemented for determining the maximal threshold value. The cumulative movement history image was generated using the proposed system depending on structural similarity estimates and ultimately, NN with a probabilistic gradient-dependent optimizer was employed for gesture categorization. In a study [36], HG recognition was accomplished through HMM and real-time tracking techniques. The hand movement was tracked using a real-time tracking technique and the hand area was extracted *via* an extraction algorithm. Furthermore, the spatial features were characterized using the Fourier descriptor, and temporal features were characterized using motion analysis. The temporal and spatial attributes were then merged for creating a feature vector. The feature vector was then extracted and HMMs were applied for recognizing HGs. About 20 diverse gestures were identified and a recognition rate greater than 90% was obtained. In a study [37], static vision-dependent HG recognition was presented. A database-oriented HG recognition was performed depending on the skin color method and thresholding technique, along with template matching *via* PCA. The hand region was initially segmented using a skin color framework in YCbCr color space and Otsu thresholding was applied for isolating the background and foreground. Then, template-dependent matching was executed using PCA for HG recognition. This approach despite providing good accuracy failed to recognize HGs in images comprising hands of other than skin color. In a study [38], procedures for recognizing four particular HGs, namely play, forward, stop, and reverse, were discussed. The HG recognition process involved different phases like image acquisition, human hand segmentation, feature extortion, and classification. Initially, a frame was captured from a webcam and skin detection was done for segmenting skin regions from the background. Furthermore, a fresh image was created comprising hand boundary, and hand geometry features were extorted for describing the HG. For gesture categorization, ANNs were used. Comparisons with diverse HG recognition techniques indicated that the proposed approach performed well, achieving 95% accuracy. In a study [39], a Kinect sensor was employed for acquiring HG images, and background segmentation of acquired HG images was done using the depth feature. Further image processing methods were utilized for determining the contour of HG-segmented images. The HG categorization was accomplished through the Naive Bayes scheme. Chao, F. *et al.* [40] presented a scheme for identifying human gestures. The gesture data was acquired through a movement-sensing input gadget and an ensemble classifier was employed for identifying every human gesture. The classifier's size was decreased using harmony search and feature selection methods for obtaining good recognition results. The experimental assessment revealed that it performed considerably well in recognizing diverse gestures. In another study [41], a methodology for identifying human gestures was proposed. An exiguous optical flow and Shi-Tomasi niche detector were exploited for tracking and identifying chief points around movement patterns in range space. A modified histogram feature descriptor and gradient locator were used for capturing the robust chief interest point. Furthermore, all the features extorted from training examples were clustered using the K-means technique, and gestures were recognized using the KNN method. Chaudhary A *et al.* [42] discussed HG recognition using appearance-based, model-based, and soft-computing-based methods. The model-based and appearance-based techniques concentrated on fingertip recognition. However, these techniques were not that effective in HG recognition when compared to soft computing methods.

The study reported that soft computing methods were effective in obtaining the exact locations of fingers or hands. In a study [43], HG recognition *via* vision-based techniques was discussed. This study stated that remarkable developments are being accomplished recently in the vision-based realm when considering the infancy of work pertinent to vision-dependent gesture recognition. However, further research related to feature extortion, classification, and diverse gesture representation is needed for strengthening the recognition process.

3. SURVEY AND EVALUATION OF HAND GESTURE RECOGNITION TECHNIQUES

HG recognition mechanisms must be capable of tracking the human hand and interpreting its motion as a useful or meaningful command. This section discusses the various HG recognition mechanisms, thus providing an understanding of the HG recognition procedure and diverse methods employed by past researchers for identifying HGs.

In a study [27], various HG recognition methodologies were discussed. The work summarized that vision-dependent gesture recognition was more feasible than glove-based HG recognition, because of the fact that sensors connected to the human gloves restricted the gestures, thereby impeding the precise gesture recognition task. In another study [44], a multimodal vision-dependent approach was devised for real-time HG recognition. The proposed vision-dependent system integrated the RGB method with a depth descriptor for classifying HGs. Two interlinked modules were employed; one for detecting the hand in the interaction region and the other for gesture recognition. Initially, user determination and hand detection were performed, followed by gesture categorization. The feasibility of the proposed approach was evaluated using an RGBD HG dataset gathered from occlusion and general illumination variation settings. Ameur, S *et al.* [45] proposed a dynamic HG recognition method specifically targeting leap motion. Spatial attribute descriptors depending on palm center and fingertip positions were extracted effectively and fed to SVM classifier for identifying the gestures. The effectiveness of the approach in identifying modeled gestures showed a greater accuracy rate (about 81%). In a study [46], distinct methods for HG recognition were presented. The canny edge detection technique was suggested for detecting points wherein image brightness changed formally or sharply. The fusion of ANNs and edge detection methods was recommended for attaining a robust and good solution for HG recognition. Truong, D. M. *et al.* [47] employed 3D CNNs for HG recognition. The efficacy of CNNs was examined on a multiview dataset comprising five dynamic HGs in indoor scenarios with composite backgrounds. Experiments demonstrated that viewpoint and background had a robust effect on recognition efficacy. Zhang, J. and Shi, Z [48]. presented an HG recognition system depending on a deep learning method and microwave transceiver. The numerous HG signals were acquired *via* a radar sensor with double receiving channels at 5.8 GHz. The received HG signals were further processed with frequency-time analysis. A deformable convolutional deep GAN was employed for gesture categorization. Experimental outputs demonstrated that this approach not merely enhanced the precise recognition rate with distinct gesture combinations but even shortened the testing time. Qi, J. *et al.* [49] proposed a HG recognition mechanism. For HG recognition, the human arm's EMG signals were acquired *via* electromyography equipment. The acquired feature dimensions were reduced and redundant data was discarded using the PCA technique. Further, static HG classification was done using NNs. Performance assessment of the HG recognition process indicated that the proposed HG recognition mechanism showed a 95.1% improvement in HG recognition accuracy. Cao, Z. *et al.* [50] presented a gesture identification method for recognizing gestures accurately and quickly from a sophisticated background. It employed a deep CNN comprising a primary module for extorting feature data, a squeeze-and-agitation network for strengthening feature affinity, and a pyramid attention network for combining context data with distinct scales. Experimental outputs reported that the deep CNN approach performed well than the remaining recognition algorithms by providing 83.45% accuracy. Lee, A. R. *et al.* [51] proposed a technique for recognizing five diverse surgical HGs like grab, one peak, hover, two peaks, and click. Capsule networks (CapsNet) were utilized for effectively recognizing surgical HGs. A comparison of the HG recognition performance of CapsNet over baseline CNN and VGG16 indicated that CapsNets outperformed the VGG16 and classical CNN techniques by providing 86.46% of categorization accuracy. Adithya, V. and Rajesh, R [52]. exploited deep CNNs for static HG recognition. The proposed deep CNN approach eliminated the necessity of hand segmentation and detection from captured pictures and decreased the computational stress experienced during human hand posture identification with traditional approaches. It intelligently derived the probable features, which discriminated the postures even with minor interclass variations. Performance evaluation of the deep CNN approach on publicly existing HG databases indicated the greater recognition potential of the deep CNN model. Araga, Y. *et al.* [53] presented a dynamic HG recognition mechanism based on Jordan Recurrent NN and hand posture categorizer. A set of HGs was modeled through a series of representative posture images. The sampled image frames were fed as inputs to the posture classifier. The Jordan recurrent NN (JRNN) was exploited for determining the gesture by identifying the temporal behavior of the posture image. The effectiveness of JRNN in recognizing the input sequence's temporal behavior was enhanced through a novel training technique. This approach was successful in recognizing reverse gestures as well. The feasibility evaluation reported that this recognition mechanism effectively recognized five gestures with 99.09% accuracy and nine gestures with 94.3% accuracy. Moreover, its recognition performance was better than other human gesture identification techniques. In a study [54], a procedure for recognizing HG based on CNN was proposed. For HG recognition, seven 3D and 2D hand motions with distinct backgrounds, mobile cameras, hand shapes, illuminations, and hand positions were recorded under short distances. Recognition performance evaluation demonstrated that training performance using CNN provided good accuracy than testing performance. Azad, R. *et al.* [55] proposed an MTS technique dependent on the movement energy of main-frames of depth sequences.

Furthermore, three-range temporal samples, namely short, middle, and long sequences containing suitable gesture data were generated. The WDMM was then proposed for extorting the spatio-temporal data from previously generated sequences through the cumulative weighted differences of successive frames. The features from WDMM were extracted *via* a local binary pattern and HOG techniques and gestures were classified by machine learning methods. Performance assessment confirmed the superiority and efficacy of the presented technique over existing gesture detection approaches. In another study [56], various HG recognition approaches were surveyed. Appearance-based representations were identified as more suitable than 3D-based representations in HG recognition systems. This study reported that the core reason behind the selection of appearance-based over 3D-based was because of the high implementation complexity associated with 3D-based recognition approaches.

4. MODELING OF HAND GESTURE IMAGES

HG recognition plays a chief part in natural human-machine interaction and nonverbal communication. It is an active field of study in machine learning and computer vision. For HG identification, several techniques have been exploited by research professionals for the modeling of HG images. This section will review such techniques for providing insight into HG recognition using HG images.

In a study by Chen, D. *et al.* [57], HG image modeling was performed using GMM, and the parameters of GMM were learned using the expectation maximum method. This approach tested five types of HGs like hand close, wrist flexion, hand open, fine pitch, and wrist extension in distinct backgrounds, as shown in the figure below:

The suggested approach recorded and split 100 pictures of each hand gesture. Each gesture necessitated the capturing of 50 photos for training and 50 photographs for testing. To improve identification, it identified HOG and Hu invariant moments using similar quantities. The K-SVD dictionary training approach was used to select atoms that represent all characteristics while minimizing computing expenses. The sparse representation method was employed, indicating that segmentation of HG images helped in enhancing the recognition accuracy. In a study [58], HG recognition from images containing 10 distinct hand gestures was implemented. Any two-dimensional cameras that support adequate picture quality may detect hand movements. Data input, pre-processing, image segmentation, feature extraction, and classification are all steps in the processing of video footage. HG images from 24 classes were considered with various space orientations. Feature extraction was performed through the Histogram of Gradients (HOG) technique. The classification was done using a sparse autoencoder and MFNN with a backpropagation method. This HG modelling approach showed good accuracy in the classification of 10 distinct HG images with both light and dark backgrounds and several hand orientations. In a study conducted by Alani, A. A. *et al.* [59], HG recognition from HG images was achieved through adapted CNNs (ACNNs). The proposed ACNN framework was trained on 3750 static HG images comprising variations in attributes, such as rotation, noise, illumination, scale, and translation. A comparison of the proposed ACNN with baseline CNN indicated that ACNN outperformed baseline CNN in HG recognition, providing 99.73% accuracy.

4.1. Interactive Image Segmentation

The significant motive of Interactive HG Image Segmentation (IS) is to perfectly satisfy the segmentation requisites of HG images without human interactions. The interactive IS schemes intend to strengthen or upgrade the recognition precision of HG identification from HG images. One such example of interactive IS for HG recognition could be the approach proposed by Chen, D. *et al.* [57] for enhancing HG recognition performance. Gibbs random field was applied to the IS and Gibbs energy was minimized through the Min-cut theorem for determining optimal segmentation. Furthermore, the segmentation outcomes of HGs yielded higher quality and better segmentation accuracy when compared with other commonly used IS techniques. According to Jia, J [60], it is divided into two sections: hand motion detection and hand gesture identification. A hand motion detection process will detect and retrieve hand movement. The current picture is matched to the prior image at a certain detection time to calculate the variance among them. It is identified if the produced variance outperforms the specified threshold warning. The fundamentals of hand movement contain specific limited characteristics, such as colour, form, *etc*. The orientation histogram is another significant aspect. It employs GMM (Gaussian Mixture Model) and expectation maximization techniques for IS.

5. MOTION RECOGNITION

In gesture identification, motion recognition also plays a chief role. Various research works have been conducted on human movement recognition [61, 62, 63, 64, 65]. This section investigates different methods exploited for motion recognition in the existing literature.

In a study [31], temporal data was encoded into motion representation, and deep features from the motion representation were extracted through ResNets for motion recognition. Bu, X [66]. proposed an approach to constructing motion posture attributes for depicting human behavior. It performed motion identification using the CNN technique. It investigated the motion performance of arms and legs in basketball actions of jumping, walking, standing dribbling, running, running dribbling, walking dribbling, ball receiving, passing, and shooting. Results reported that the proposed CNN technique not just reduced attribute dimensionality but even provided higher discrimination. Zhou, Y. and Gao, Z [67]. proposed an automated motion recognition technique based on CNN for clinical motion images. Initially, manual features were extracted and then CNN was used for extracting motion data from clinical motion images. Furthermore, convolutions were learned through applying extreme learning machine to CNN and earlier extracted manual attributes. The attributes were fused for representing the movement/motion characteristics of clinical motion image sequences. Simulation outcomes revealed that the proposed motion recognition technique effectively boosted the recognition accuracy of small-scale motion in clinical motion images. Patrona, F. *et al.* [68] developed a framework for human action identification, recognition, and assessment of motion data. Kinematics information and pose data were utilized for information description. Dynamic and automatic weighting and kinetic energy-dependent descriptor sampling were employed for effective action segmentation and its labelling. The intelligently segmented and identified action instances were evaluated by the proposed action assessment framework and compared with reference frameworks for determining their similarity. Fuzzy logic was employed for providing indicative feedback with relevant instructions on executing the actions more precisely. Experimental simulations illustrated clearly that this approach outperformed the state-of-the-art techniques by 0.5 to 6%. In a study by Rimkus, K. *et al.* [69], hand motion detection was achieved by capturing data *via* a kinect device and gesture identification by Neural networks. Ten particular single-hand movement gestures iterated several times by 7 distinct people were considered in this study. However, this approach failed to detect certain gestures because of the huge heterogeneity of individual human movements. In a study by Gao, L [70], motion recognition was accomplished *via* wearable sensor technology. The human motion information was acquired through movement capture sensors and WSNs. For motion recognition characteristics of distinct posture signals were studied and signal feature sequences were selected for determining posture signals. Furthermore, a multilevel gradable human posture recognition technique was exploited for precisely recognizing diverse human poses like squatting, running, sitting, and walking. The proposed movement recognition approach showed faster speed and greater recognition rate than conventional recognition algorithms. Another study [100] examined topologies of adversarially trained deep Convolutional Networks (ConvNets) for video action recognition. The problem is to collect the extra details on appearance from stationary images along with movement across frames. It presents a two-stream ConvNet design that includes both time and space networking. Then, despite minimal training data, a ConvNet based on cross-dense optical flow may obtain extremely excellent performance. Lastly, it illustrates how multitask learning may be utilised to enhance the quantity of training information and boost efficiency on two separate action categorization datasets. This structure has been trained and assessed using the industry-standard video action benchmarks UCF-101 and HMDB-51, in which it is comparable with the best. It also outperforms prior attempts to employ deep nets for video categorization by a large edge. This hypothesised topology is similar to the two-streams theory that states that the human visual cortex has two routes: the "ventral stream" that recognises entities and the "dorsal stream" that identifies movement.

Table 1. Comparative study of existing studies.

References	Objectives	Recognition Task	Techniques Used	Results Obtained	Future Directions
[31]	To recognize gestures through multidimensional attribute learning.	Motion and gesture recognition	CResNets, CLSTM, linear fusion	Recognized gestures effectively through exploiting the entire complementary benefits embedded in depth cues and RGB, specifically with respect to generalization and efficiency.	Pose variation must be included and improvement in classification accuracy is needed for scenarios containing distinct gestures with motions along the same direction.
[45]	To perform HG recognition.	HG recognition	SVM	Achieved 81% accuracy in the identification of modeled gestures.	For dynamic gesture identification, temporal data in addition to spatial data should be considered.
[47]	To evaluate the robustness of 3D CNNs in HG recognition.	HG recognition	CNNs	Exhibited higher performance with regard to HG recognition in frontal view.	To match the unfamiliar gestures with the known ones for enhancing HG recognition accuracy.
[57]	To enhance the HG recognition	HG recognition	Interactive IS, GMM, Expectation maximum method, Min-cut method, Gibbs random field	Provided higher image quality and better segmentation accuracy.	Techniques for reducing several interferences (like image distortions, shadows, and highlights) should be inspected and the recognition rate should be improved.
[58]	To perform gesture recognition.	HG recognition	HOG, MFNN with backpropagation method, Sparse autoencoder	Achieved 92.5% accuracy in HG recognition.	Implementation and performance testing of gesture recognition should be conducted by exploiting larger databases with more gestures and samples, hand space alignments, and diverse backgrounds.
[59]	To perform HG recognition	HG recognition	ACNNs	Showed 99.73% accuracy in HG recognition and an improvement of 4% over baseline CNNs.	Performance should be assessed with regard to real-time HG classification.

(Table 1) contd.....

References	Objectives	Recognition Task	Techniques Used	Results Obtained	Future Directions
[66]	To recognize motion gestures.	Motion recognition	CNN	Achieved 96% motion recognition accuracy.	Motion recognition performance for handling more motion gestures should be examined.
[68]	To perform motion recognition.	Motion recognition	Kinetic energy-dependent descriptor sampling, fuzzy logic	Outperformed state-of-the-art techniques by 0.5 to 6%.	Performance should be assessed for diverse human motions.
[69]	To perform motion recognition.	Motion recognition	Neural networks	Flexible and easily adaptable for human gesture interpretation.	Recognition accuracy should be further improved.
[70]	To recognize human motion.	Motion recognition	Multi-level gradable human posture capture method	Achieved greater recognition rate and performed faster recognition than classical recognition techniques.	Further improvement in the motion recognition rate is desired.
[71]	To recognize HGs.	HG recognition	3D CNN, geometry algorithm	Performed well in complex backgrounds and varying light levels.	Should be extended for handling more HGs.
[72]	To identify HGs.	HG recognition	EMG signals, CNN	Achieved 99% accuracy in HG recognition.	Execution time should be enhanced.
[73]	To recognize diverse human gestures.	Gesture recognition	Multi-stream CNN	Outperformed the conventional surface EMG signal-dependent gesture identification methods.	Further extension is required in terms of multi-label, multi-view gesture recognition.
[74]	To perform HG recognition.	HG recognition	Mechanomyography signals, CNN	Provided 94% accuracy in HG recognition	Further optimization is needed in gesture categorization accuracy.
[75]	To identify diverse HGs.	HG recognition	Support vector Machine (SVM), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Decision Tree (DT)	Showed promising outputs achieving average gesture categorization accuracy greater than 80%.	Must be extended for handling more HGs.
[76]	To identify HGs.	HG recognition	HOG, correlation technique	Attained a 79% recognition rate.	The recognition rate should be further enhanced.
[77]	To perform real-time gesture identification.	Gesture recognition	Multi-channel CNN	Achieved a higher gesture categorization rate.	Gesture identification by including two-hand gestures from multiple subjects should be examined.
[78]	To perform real-time HG recognition on EMG signals.	HG recognition	ANN	Achieved 90.7% recognition accuracy outperforming classical recognition techniques.	Computation using confined processing and memory resources without compromising recognition precision must be executed.
[79]	To recognize static HG.	HG recognition	Edge histogram, SVM	Achieved a 93.75% success rate in HG categorization.	Dynamic HG should be recognized.
[80]	To perform real-time HG recognition.	HG recognition	Vision-based scheme	Performed accurate and robust HG recognition in static background.	HG recognition in dynamic settings should be implemented.
[81]	To devise an HG recognition mechanism.	HG recognition	CNN	Exhibited 98.15% in HG recognition.	Performance should be tested for recognizing more HGs.
[82]	To recognize dynamic 3D HGs.	HG recognition	CNN, ResNets	Showed 98% accuracy in dynamic HG recognition.	More HGs should be incorporated for evaluating the HG recognition method's efficacy.
[83]	To recognize dynamic gestures.	Gesture recognition	Directional Pulse combined Neural Network	Provided a greater recognition rate and minimized computing time.	Further optimization is desired for complex gesture recognition.
[84]	To execute HG identification in videos.	HG recognition	Deep attention-based ResNets	Recognized HGs with greater accuracy.	Pre-trained networks trained on distinct activity recognition databases should be utilized for assessing the recognition robustness.

(Table 1) contd.....

References	Objectives	Recognition Task	Techniques Used	Results Obtained	Future Directions
[85]	To optimize HG recognition performance.	HG recognition	Transfer learning-dependent CNNs	Outperformed the best available recognition work, achieving 98.09% accuracy.	More HG features must be included and their recognition performance should be analyzed for determining the productiveness of the approach.
[86]	To perform HG recognition.	HG recognition	Sliding window, NNs	Achieved 90.1% accuracy in HG recognition.	Recognition accuracy must be further boosted.
[87]	To recognize hand posture.	HG recognition	Feature fusion-dependent CNN	Outperformed the related techniques on distinct standard datasets.	Recognition results must be enhanced.
[87]	To detect HGs.	HG recognition	ANN, CNN	Recognized HGs effectively.	The approach should be extended for recognizing more hand movements.
[88]	To identify gestures revealing joint and muscle pain.	Gesture recognition	NNs	Showed a 91.9% recognition rate.	Complex joint and muscle pain recognition using a larger gesture dataset.
[89]	To recognize faces and HGs.	Face and HG recognition	NCC r-g colour space, NNs	Provided accurate outputs achieving a 93.6% recognition rate.	Techniques for eliminating the diverse interferences encountered during face and HG recognition tasks should be used.
[90]	To recognize sign language and HGs.	Sign language and HG recognition	LSTM	Performed recognition effectively.	More data like skeleton features and RGB information should be included.
[91]	To recognize HGs and convert voice for the well-being of mute and deaf people.	HG recognition	Computer vision, Machine learning, CNN	Achieved 86% recognition accuracy.	Work should be extended with regard to Indian and other sign language recognition.
[92]	To recognize gestures.	Gesture recognition	Mm-wave sensor, Random forest (RF)	Showed increased robustness and accuracy.	The recognition process should include more features revealing better recognition outputs.
[93]	To recognize real-time gestures.	Gesture recognition	Quadruple visual interest point method	Showed robust recognition in terms of clothing type, gesture type, motion characteristics, and motion trajectory extent.	Improvement in recognition results is required.
[96]	To detect HGs.	HG recognition	Spike convolutional recurrent NN (SCRNN)	Achieved 96.59% and 90.28% accuracy in 10 class and 11 class gesture categorization.	Human motion/action recognition should be executed.
[95]	To recognize hand posture.	HG recognition	PCA	Recognized human hand postures effectively.	Temporal constraints should be incorporated during gesture recognition.
[96]	To recognize human gestures when several moving subjects are present.	Gesture recognition	Radar sensor, Dopple-range processing	Effectively identified human gestures even in the presence of interferences from nearby moving targets.	Better gesture categorization and recognition techniques should be included for further upgradation in recognition outcomes.
[97]	To recognize human gestures.	Gesture recognition	Radar, CNN	Provided excellent recognition outputs with only diminutive training effort.	Gesture identification performance should be evaluated in cluttered settings.
[98]	To extract human gesture characteristics.	Gesture recognition	Visualization technique	Effectively extracted human gesture characteristics.	A recognition procedure for visualized gestures should be developed for interaction between virtual characters and computer users.
[99]	To recognize spatio-temporal gestures in degraded environments.	Gesture recognition	3D integral imaging	Efficiently detected human gestures in low illumination environments and in partial occlusions.	The identification of sophisticated human gestures in diverse degraded conditions must be investigated.

(Table 1) contd.....

References	Objectives	Recognition Task	Techniques Used	Results Obtained	Future Directions
[101]	To recognize human motion pose by extracting the location of key joint points on the image.	Motion gesture recognition	Adversarial Network Algorithm	It tackles the problem of massive deformations of portions of the body, while simultaneously considering the intricacy of multiple levels of body components. It aids in reliably estimating the locations of various body parts, particularly those that are deformed or substantially obstructed.	To address the issue that the algorithm is light-sensitive.
[102]	To recognize vision-based hand gesture	Hand gesture recognition	Deep learning techniques	It uses vision-based hand gesture recognition as a precursor to sensor-based data acquisition methodologies by using a still/video camera.	A scope can be increased by allowing the use of both hands.
[103]	To recognize robust vision-based hand pose	Hand gesture recognition	ToF sensor, a Real-time method based on optimized shape representation	It produces good results with its varied selection of egocentric hand gestures. It includes a module for estimating hand posture based on depth map data, in which the hand silhouette is first retrieved from the exceptionally precise and accurate depth map.	The learning model should be improved so that the recognition system can identify a larger variety of gestures, *i.e*, not limited to the gestural lexicon.
[105]	To explore different gesture recognition and detection techniques.	Gesture recognition	CNN, HOG, OpenCV	It enables users to utilize hand gestures to engage with its applications.	It is fixed with unchanging background and region-specific, which needs to be addressed.
[106]	To recognize multi-feature gestures based on real-time methods.	Gesture recognition	LSTM, SFTF	It provides a real-time recognition approach of multi-feature gestures based on a long short-term memory network to tackle the issues of classical pattern recognition and has a 93.50% recognition accuracy for simple and complicated gestures	It has excellent results for gesture recognition and also time management compared to traditional methods.
[108]	To recognize hand gestures in data scarce environment.	Hand gesture recognition	Feature extraction, shape matching algorithms	For real-time applications, it offers a fair balance of accuracy and computing efficiency.	Fast search methods could be explored for image retrieval purposes.
[110]	To recognize gestures based on hand skeleton tracking	Hand gesture recognition	Jaccard Index, Transformer network-based method	It developed a fresh dataset with diverse motions comprising varied kinds and lengths. In an online recognition situation, motions must be discovered throughout sequences.	These datasets can be used for future enhancements.
[111]	To recognize signature by in-air hand gesture	Dynamic signature recognition	Transfer learning	In identifying HGS, it can obtain 99.03% precision and 98.89% recall and demonstrates its resilience in dealing with various types of forgery assaults, such as random and skilled forgeries.	The signature continuity can be further explored.
[113 - 116]	To recognize hand gestures through HCI	Hand gesture recognition	EDenseNet	It obtains 98.50% average accuracy without augmented data and 99.64% average accuracy with augmented data, outperforming other deep learning-driven instances in both settings, with and without augmented data.	Advanced color segmentation can be addressed.

6. COMPARATIVE ANALYSIS

The recently reviewed works (*i.e.* from the year 2015 to 2021) considered in the current survey are depicted in Fig. (**3**). Fig. (**4**), presents that more number of technical papers (*i.e.*, 17 papers) published in 2021 are considered in this study, followed by papers (14 papers) published in 2019 and 2020, 2018 (12 papers), 2017 (10 papers), 2016 (7 papers), and 2015 (6 papers) (Fig. **5**).

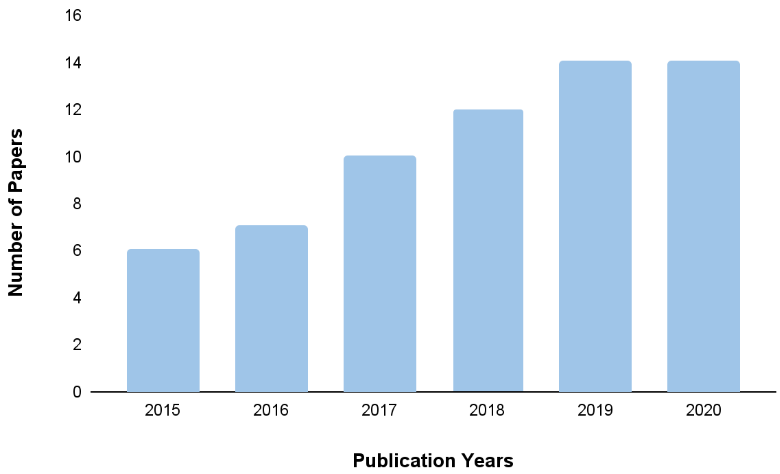

Fig. (3). Five hand gestures for recognition.

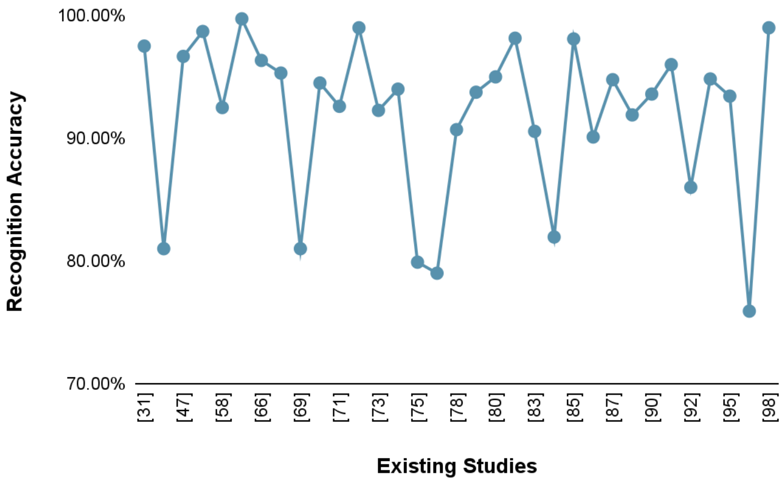

Fig. (4). Hand gesture recognition framework.

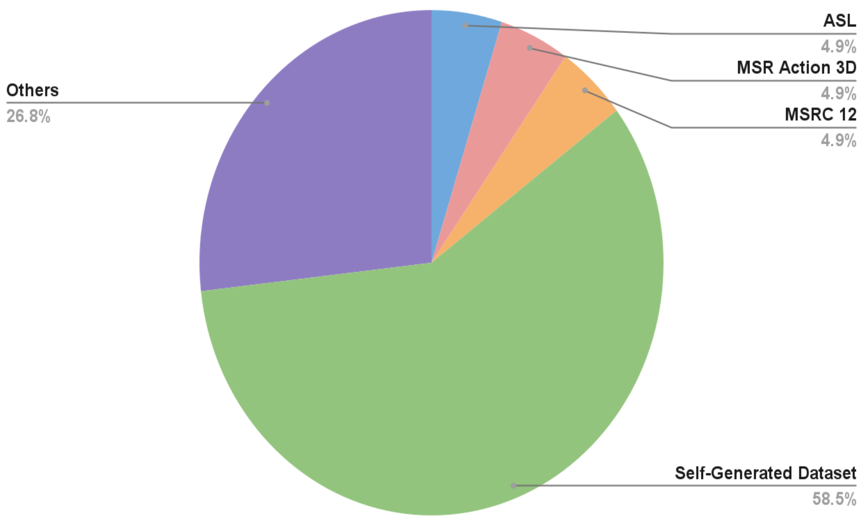

Fig. (5). Recently reviewed studies.

CONCLUSION

Gestures are a diverse means of interaction that deliver more creative, natural, and perceptive methods for communicating with machines. Human gesture and motion recognition are largely exploited recently for modeling and recognizing human actions. Gesture recognition, particularly hand posture, and HG recognition are employed for non-verbal interaction between machines and humans, physically challenged and healthy people. This paper described the gist of human gesture and motion recognition in analyzing diverse human actions. It reviewed several studies on human gesture design and explored diverse design methodologies exploited for gesture image segmentation and gesture recognition. The distinct approaches like vision-based, sensor-oriented, assumption-based techniques, soft/intelligent computing methods, *etc*. utilized for analyzing HG images and human motion identification were also studied. The vision-driven methods provided good recognition outputs but experienced certain hardships. The vision-driven HG/motion recognition techniques hugely relied on image sensors' sensibility and therefore the reasonably weak image quality impeded their development. Moreover, some image processing methods were ineffective in performing the IS correctly and those which met the accuracy requisites involved many human interactions, and thus were inefficient for real-time applications. The sensor-oriented methods yielded good recognition outcomes but captured only specific data and ignored other details imperative for gesture modeling. The approaches relying on various underlying assumptions were suitable and applicable in a controlled lab environment but were not generalizable to random settings. Some general assumptions considered by most works included ambient lighting settings and high-contrast static backgrounds. However, these assumptions were inapplicable in dynamic settings. In instances wherein the actual positions of hands are unable to obtain through conventional recognition schemes, soft computing techniques performed extremely well in providing the anticipated outputs. However, even these technologies require up-gradation for attaining superior recognition results. Thus, through designing better technologies that could overcome the recognition hardships faced in existing methods and upgrading the available recognition techniques by combining the advantages of diverse recognition approaches and incorporating additional features, improved and desired recognition outcomes could be obtained.

LIST OF ABBREVIATIONS

DNNs	=	Deep Neural Networks
LSTM	=	Long Short Term Memory
GAN	=	Generative Adversarial Networks
RNNs	=	Recurrent Neural Networks
MFNNs	=	Multi-layer Feedforward Neural Networks
ResNets	=	Residual Networks
CNNs	=	Convolutional Neural Networksa
NNs	=	Other Neural Networks

CONSENT FOR PUBLICATION

Not applicable.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest, financial or otherwise.

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