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ANALYSIS ON HAND GESTURE RECOGNITION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The main goal of gesture recognition research is to create a system that can recognize specific human gestures and use it to transmit information or to control the device. Human-computer interaction needs to use various methods, such as location, voice, gestures, lip development, facial joints, etc., and coordinate them to provide an increasingly vivid customer experience. The visual interpretation of gestures can be used to complete the natural human-computer interaction. In this article, we propose a method for recognizing gestures. We have designed a system that can recognize specific gestures and use them to transmit information. We have used backward propagation and training algorithms based on supervised feeding neural networks to classify gestures. A neural network program was developed in MATLAB, which can recognize the number of fingers and achieve correct results of 95.4% testing accuracy. An effective and effective gesture recognition method is proposed. The hand area is detected by background subtraction. Then spread your palm and fingers apart to identify your fingers. After recognizing fingers, you can classify gestures with a simple ANN classifier.

KEYWORDS

Human Computer Interaction, ANN, Hand Gesture Recognition System, Feature Extraction.

1. INTRODUCTION

Computer systems and interfaces are the emerging technologies and are dispersed in various fields rapidly. Human ability in adopting computers and information systems is an expanding research topic. This interdisciplinary domain relating the human attitude and computer is termed as Human Computer Interaction (HCI). Hence a primary objective of HCI is generating methods that amalgamate the attitude of the human and the computer to produce interactive system, shifting the technology from processor centric user computer-interface to human-centred multimedia, multi-mode co-operative skill, incorporating lip reading, tracking of head movements, recognition of hand gestures, facial recognition, body interaction recognition etc. Lacking dedicated devices for tracking, amongst the biggest concerns for the system becomes accurate assessment and validation of hand movement through vision detecting sensors and hardware. A tracking procedure utilizing vision-based input requires only an appropriate vision sensor, essentially a camera. Generally, the overall framework of this approach should ideally be simpler and lighter as compared to the Data Glove procedure, and should facilitate interaction without requiring any complementary hardware. This sort of interaction can be difficult in the context of computer Pattern and vision analysis, given its natural associated complexities with algorithmic issues, i.e. segmentation of images, extraction of features, and calibration of the camera device etcetera. The HCI is generally dependent over the finger point detection or depending on the finger point position which confines the normal means of manipulation using hands and results in complicating the easy task. One best example is the usage of a computer mouse which requires the clicking of the mouse and moving it in the 2D space. The mouse rotation operation to control the movement of the cursor is not realized directly by humans.

Because analysts use neural networks in their work to gain many benefits. Design appreciation is a great method that can use material in data or summarize it. Neural networks study to identify patterns in datasets. The scheme was settled over knowledge relatively than indoctrination. Programming is time intense for experts or obliges analysts to specify precise behaviour of the model. Neural networks can learn data patterns, allowing analysts to do more interesting work. In a constantly changing environment, neural networks are very flexible. Rule-based schemes or programmed classifications are inadequate to situations used in the design; when the situations change, they will no longer be valid. Although neural networks may take a while to learn about sudden changes and sudden changes, they are very good at adapting to changing information. Compared to traditional methods, neural networks can build more information models. Since neural networks can knob very compound connections, they can simply perfect data that is hard to model using traditional methods (such as inferential statistics or indoctrination logic). Neural network performance is at least as decent as classic arithmetic models, and most problems are improved. The model established by the neural network can better reflect the structure of the data in a shorter time. The neural network can now run normally on the corresponding computer hardware. Despite the large amount of computation on the neural network, these routines have been optimized so that they can now be run on an individual computer within a reasonable time. They don't need a supercomputer like primary days of neural network research (Kabir et al., 2019; Yan et al., 2012).

Feed - Forward Networks: A neural network without feedback loops is termed as feed forward neural networks or perceptions. The previous perceptions training algorithm converges if a solution to a problem exists. This limitation showed to be uncertain necessitating that the classification

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has to be linearly distinguishable. This drawback was surmounted by the Back propagation algorithm. This algorithm trains layered networks. In a layer network, one layer exists between input and output. A feed forward network is shown in figure 6.2, where data are applied at the input nodes and proceeds toward the output node. Nodes 1, 2 and 3 are input nodes, nodes 4 and 5 are hidden nodes and nodes 5 and 6 are output nodes. Back Propagation Algorithm (Steepest Gradient Technique) is the most common Neural Net algorithm which is a multilayer network. The algorithm applies a weight modification based on the sigmoid function. Back propagation is a supervised learning where expected output is known. The Back propagation algorithm is an evolution of Windrow-Hoff algorithm. It employs the gradient descent technique to reduce the minimum square error. The minimum square error is mainly due to the difference among real and trained output from the net. In the Back propagation algorithm, the input is applied to input nodes of the network. The input propagates through the hidden nodes towards the output nodes of the network. The response of each input node is thus obtained at the output node. The actual output of each output node is then compared with the trained or the desired output. If there is no difference the training of the network stops else the iterative process of changing the weights of the nodes are performed until the difference between the actual and the trained outputs is minimized (Liang et al., 2015; Rokade et al., 2014).

Figure 1: One layered neural net structure.

2. RELATED WORK

Every nation has its very own Sign verbal. Irish Sign Language is exclusive in relation to British Sign Language or American Sign Language. Isolate, there has been a huge measure of research on hand signal acknowledgment. A portion of the prior motion acknowledgement frameworks endeavoured to recognize gestures utilizing glove-based gadgets that would quantify the position and joint points of the hand. Notwithstanding, these gadgets are extremely awkward and as a rule have numerous links associated with a PC (Dardas et al., 2011). This has delivered the inspiration of utilizing nonintrusive, vision-based methodologies for perceiving gestures. Vision-based methodologies include utilizing at least one camcorder to catch an individual signalling and utilizing PC vision procedures to decipher very specific motion. A dream based motion acknowledgment framework can be separated into three fundamental segments: hand signal displaying, hand motion examination, and hand motion acknowledgment. The signal model portrays how the hand motion is to be spoken to. The kind of utilization wanted significantly affects the sort of model that must be Picked. On the off chance that an application with just a few gestures is required, at that point a Straight forward model can be utilized. Be that as it may, in an application with a vast motion set, for example, gesture based communication Acknowledgement, a progressively point by point model will be required. Notwithstanding, there are exchange offs in picking an increasingly mind boggling model as will be examined later. In the wake of picking a model, the investigation is performed to register the model parameters from the picture includes that are separated from the video input streams. The investigation organization is trailed by the acknowledgment stage, which orders the model parameters, delegate of a particular motion while thinking about the model and at times sentence structure. The objective of the investigation is to identify and gauge highlights from the video succession pictures so as to appraise the model parameters. The investigation stage would thus be able to be separated into two noteworthy segments: include discovery and parameter estimation.

Gesture recognition using shallow EMG signals can be realistic to various situations, such as member prosthesis resistor, human-machine interface, etc. In this article, we propose a gesture gratitude technique that uses single-channel rods to classify 5 gestures: pinch, finger stretch, fist, wave hand, and wave hand. The process includes 4 steps: pre-processing, data subdivision, feature extraction, and classification. In the pre-processing step, a power movement discovery algorithm is practical to remove the rest of facts set. In the data segmentation step, the overlay window

algorithm is applied to segment the main window to get sub-windows. In the feature extraction step, a portion of the features is observed from the previous sub window. And extract the time domain characteristics of the original surface EMG signal as an extra portion. Finally, for organisation, the artificial neural network is modelled to mark sub-window observations. Experiments show that the precision of this method is 91.3% (Sheng et al, 2019).

All time among 250,000 and 500,000 people universally suffer plain spinal cord injuries, many of which can cause movement disorders. A group of physical gestures can contain all language, making it an effective means of communication for people with sports disabilities. Best gesture recognition systems involve users to learn specific gestures specified by scheme. It turns out that this is the main disadvantage of these systems, because the movement of most people with movement disorders is severely restricted. Therefore, they may not be able to complete certain system-defined gestures. Therefore, in this article, we suggest a real-time scheme that can be modified for specific dynamic movements of the user's hand. The scheme can be charity to perform certain tasks. Use the Haar waterfall uncovering algorithm to track hand movement and tracking path. The Siam Neural Network is recycled for personalization and gesture recognition (Muralidhar et al., 2019)

Gestures are single of simplest or most sensitive means of statement between people and computers in the real sphere. In our daily life cycle, we habit many motions to express our intentions. Hand or face gestures are the greatest significant means of human non-verbal communication. In recent years, much progress has been made in developing gesture recognition using machine interfaces. Using artificial neural networks, a system for gesture recognition was developed in the pad laboratory. Here, the dataset is composed through many gestures or complete color-based separation, or many forms operation gestures are segmented from the input image. Here, chin withdrawal is based on "gradient histogram" technique. After dissection, gestures or labels are divided into left-handed and right-hand gestures. This will be passed to the neural network for exercise, and train-rp is a purpose used to train gestures. During the test, the facial video is provided to scheme, or classification will recognize conforming production in box or predict it (Eshitha et al., 2018).

Gestures deliver an ordinary way for persons to relate with processors to run various submissions. However, features such as complication of the gesture structure, the size of the hand, the difference between the gestures and the ambient lighting will affect the performance of the gesture recognition algorithm. The latest progresses in deep knowledge have knowingly improved presentation of double gratitude systems. In particular, compared to old-style mechanism learning methods, deep convolutional neural networks show excellent performance in image representation and classification. This article suggests an adaptive deep convolutional neural network proper for gesture gratitude chores. The data enhancement feature was originally practical, which can randomly move the image horizontally and vertically to 20% of the original size, digitally growth size of dataset, or increase strength required for deep learning methods. These pictures are introduced into planned ADCNN typical, which eliminates problem of data overfitting through network initialization (ReLU and Softmax) or presence of L2 regularization. After these modifications, investigational grades using ADCNN model show that this is an actual technique to improve presentation of CNN gesture recognition. The model was skilled or tested using 3750 static gesture images, which included changes in scale, rotation, translation, lighting, or sound. When comparing planned ADCNN with the reference convolutional neural network, results show that:

The planned ADCNN achieves an organisation recognition accuracy of 99.73%, which is 4% higher than the reference convolutional neural system model (95.73%) (Ali et al., 2018).

Gesture recognition by locator has been broadly used to control electrical equipment, military equipment, etc. In this article, we study the feasibility of using an improved deep convolutional neural network to merge many time occurrence autographs (integrating micro-Doppler signatures, range time signatures, or angle time autographs into the spectrogram) to recognize the gesture.

Sex Several typical gestures were measured using millimetre wave radar, including scale, double pressure, clockwise and counter clockwise rotation, and their spectrograms were studied. Among them, use EDCNN to categorise spectrograms, 80% of data is used for exercise, or remaining 20% of the data is used for verification. The simulation shows that the classification precision of this method is 96.2% (Feng et al., 2019).

3. PROPOSED METHOD

Gestures are a type of body language commonly used as a means of statement, or are very serious in human-computer interaction. Vision-based gesture recognition systems for detecting hand movements are essential to provision such networks. Gesture recognition can provide a convenient or usable edge among the device or the user. In our method, we use a neural system to identify different gestures, which is a connection of interconnected nodes consisting of 3 layers (input layer, hidden layer, and output layer). The given idea is propagated through the network to provide the desired output. First, we must train the neural network to recognize different gestures. So we have given 100 different sample images inputs to obtain the different outputs. Initially the dataset is loaded into the network for training. Pre-processing is done before the feature is extracted. The training is done in a neural network after training an input image. The given input image is tested for recognizing the gesture. A confusion matrix is produced accordingly to the produced output with its mean accuracy. The 1st innovation of planned technique is that gesture recognition is created on results of finger gratitude. So, recognition is done through simple or effective rule classifiers rather than complex and complex classifiers (such as ANN). Some previous jobs required users to wear data gloves to get gesture data. However, a dedicated sensor of the data glove is classy or makes it difficult to apply it widely in real life. In this work, the author uses a TOF (Kinect sensor) camera to detection depth of atmosphere or uses a different tape on the wrist to detect the area of the hand. Our method uses only ordinary cameras to capture the visual information of gestures, without the help of an exceptional tape to detect the area of the hand. (Iii) The third advantage of the proposed method is that it is effective or suitable for real-time requests.

3.1 Artificial Neural Networks

The neural network approach is based on the elementary processors called neurons. Each neuron takes many efforts or produces one crop. All effort is related with a mass and the harvest is the prejudiced amount of inputs. The production purpose may be separate or constant. The inputs are represented as v_1, v_2, v_3 , and the bulks are represented by w_1, w_2, w_3 . The sum of all inputs to a neuron is given by

$$x = \sum v_i n_i = 1 w_i \quad (1)$$

Where x is the threshold of a neuron. A transfer function $f(x)$ is defined with a neuron which gives an output. These neurons are interconnected such that they take a number of external inputs and deliver some number of outputs. The applications of these networks are classification, auto association and general association.

$$E = \sum \sum (y_j i - d_j i) \quad (2)$$

Where $y_j i$ is the actual production of the output node and $d_j i$ is the wanted output of the similar output node of the network. Steepest gradient descent technique is applied to update the weights of the network

$$w_{i,j}(k+1) = w_{i,j}(k) - \eta \partial E(n) / \partial w_{i,j} \quad (3)$$

3.1.1 Image Pre-Processing

By adjusting the intensity of the image to highlight the target area, that is, the visual area that is diseased after the data collection is complete, the image quality can be improved. The histogram equalization algorithm (CLAHE) is used to enhance the image.

3.1.2 Image Segmentation

Three groups are predictable from the image of leaves, related, infected groups, or greens. We apply K-means gathering on hue components of HSV pictures.

3.1.3 Feature Extraction

Function plays a vital character in distinguishing one illness from one more. We mean to use color characteristics such as the mean or standard deviation. We also plan to use texture features such as kurtosis, skewness, cluster highlights, and cluster shadows. To extract texture features, a grayscale match matrix will be used.

3.1.4 Classification

The classification assigns data to precise clusters or classes. Classification is generally called the managed learning method. Classification is a two-

step process: First, a classifier perfect is created, which describes a predefined set of classes. This step is called the learning phase (training step), where the classification algorithm matures a classifier by "learning" data with specific class labels. In the 2nd step, use the perfect produced in the first period for classification. The overall view of the motion gesture recognition. The webcam captures the live video streams of the hand. Segmentation using skin colour or the motion or both together is carried out to detect the hand. Detect the finger or the colour caps on the finger. As the focus is on the motion gesture recognition, the finger tips are to be detected accurately to trace the pattern drawn in the air. Hence the marker has to be detected accurately. Here two markers are used

Figure 2: Proposed Flow Chart

One of the markers is used to guide the pattern and another to indicate start and stop operation. Two solutions exist for detection of the marker: i. Detection of the finger tip, utilizing it as a primary marker in collaboration with the thumb, ii. Cladding the two fingers with different coloured caps. Both procedures shall be tested for efficiency and accuracy, whilst the superior one based on the results will be selected. The marker coordinators in following frames are assessed and utilized to convert over to binary image. Morphological operations and filtering is performed to remove the unwanted noise. The important features are extracted from the pattern drawn by the figure. The classifier is trained to Artificial Neural Network (ANN) classifiers are tested and the best is used the recognized pattern is used to perform relevant operation like hand mouse and to assist patient on bed in special ward

4. RESULT DISCUSSION

Subsequent to displaying and examination of the input hand picture, gesture classification technique is utilized to perceive the gesture. Recognition process influenced with the correct choice of highlights parameters and appropriate arrangement calculation. For instance edge identification or shape administrators can't be utilized for signal acknowledgment since many hand stances are created and could deliver misclassification. Euclidean separation metric used to group the gestures. Factual instruments utilized for signal characterization. Neural system has been generally connected in the field of removed the hand shape, and for hand signal acknowledgment. The implementation and performance evolution of the proposed algorithm is done in MATLAB Software.

Figure 3: Hand Gesture Process

Figure 4: Hand Gesture feature extraction figure count

Figure 5: Hand Gesture noise additions noise

Figure 6: Hand Gesture feature extraction

The hand uncovering output is a binary image, where white pixels are followers of hand area and the or black pixels belong to related. An instance of hand detection results is shown in Figure 3. The following process is then performed on the binary image of the hand to part finger or palm. Finger or palm division. With palm cover, fingers or palms can be simply separated. The part of the hand covered by the palm is the palm, while the rest of the hand is the finger. Table 1 shows the results of segmentation of fingers or palms.

In the segmented finger image, a marking algorithm is applied to mark the finger area. In the result of the labelling method, the detected area with very few pixels is considered a noisy area and is discarded. Only areas of sufficient size are considered fingers and are retained. For each remaining area, the finger, there is the smallest bounding box surrounding the finger. Finger content means which fingers can be perceived. The rule classifier is very actual. For example, if 3 fingers are detected, namely central finger, ring finger and little finger, gesture is classified in Table 3

Table 1: Feature extracted from input image

Sl.No	Input	Addition of Noise	Feature Extraction
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			
16			
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22			

When a finger is detected and recognized, a simple rule classifier can be used to recognize the gesture. In ANN classifier, predicts gestures based on the number and content of detected fingers

Table 3: Detailed Accuracy Measure for Gestures

Gesture	No. of image	Correctly classified image	Incorrectly classified image
One Finger	4	4	-
Two Finger	5	5	-
Three Finger	4	4	-
Four Finger	5	4	1
Five Finger	4	4	-
TOTAL	22	21	1

$$\text{Accuracy} = 22 - 1 / 22 * 100 = 95.4\%$$

To evaluate the proposed model, the proposed model was tested in an experimental setting. Gestures based on five-digit gestures were systematically tested. The simulation results show that the average recognition rate of gesture recognition of this system reaches 95.4% testing accuracy. Table 3 Accuracy of the gesture recognition model

Table 4: testing Accuracy comparison for The Proposed Model According

Model	No. Of Person	Accuracy
Previous work [Raihan Kabir][1]	10	94.5%
Proposed work	22	95.4%

Table 2: Finger count from input image

S.no.	Input image	Finger Count
1		Finger Count 1
2		Finger Count 1
3		Finger Count 1
4		Finger Count 1
5		Finger Count 2
6		Finger Count 2
7		Finger Count 2
8		Finger Count 2
9		Finger Count 2
10		Finger Count 3
11		Finger Count 3
12		Finger Count 3
13		Finger Count 3

14
15
16
17
18
19
20
21
22

5. CONCLUSION

In this Research work, propose a strategy for arranging static hand gestures utilizing hand picture form where the main highlights are that of low-level calculation. Utilizing Skin shading division gives great outcomes to disengage forefront from foundation. This strategy is vigorous against comparable static gestures in various light conditions. The significant objective of this examination is to build up a framework that will help in the cooperation among human and PC using hand gestures as a control direction. Additionally after the option of commotion it shows motion results. Hand signal acknowledgment based man-machine interface is being grown vivaciously as of late. Signal acknowledgment is likewise significant for creating elective human PC communication modalities. It empowers humans to interface with machines in a progressively common manner. MATLAB gives the better answer for hand signal acknowledgment. Sign Gesture Recognition has been effectively done in MATLAB. In view of the proposed strategy the normal acknowledgement rate is highly contrasted with the current strategies. Hand gestures acknowledgment was performed for 22 subjects by fixing the camera at fixed tallness. Great lighting was furnished utilizing ablaze light with nun mistakable white foundation for both the picture handling techniques. Subjects were told to indicate fingers looking like the checkof1, 2,3,4 and 5. The hand gestures were perceived productively with least mistake rate by the picture preparing strategy, utilizing ANN calculation. To indicate the potency and effectiveness of the proposed system results performance are compared with existing work with 94.5% and it's been analyzed that the proposed algorithm had achieved highest testing accuracy with 95.4 %.

Future work will incorporate execution, execution examination and improvement of structured systems for extended database, with bigger number of tests and gestures, different foundations and hand space
Future Scope: The presentation of planned technique is very dependent on results of manual discovery. If there are affecting objects with a colour similar to that of skin, these substances will appear in the detection result of hand, thus reducing presentation of gesture recognition. However, machine learning algorithms can distinguish hands from background. ToF cameras provide depth material that can recover hand detection performance. Therefore, in future work, machine learning methods and ToF cameras can be used to solve complex background problems or improve sturdiness of manual discovery.

Findings: One of difficulties in gesture recognition is commerce related to image and the sound that often appears in the region of interest (such as the hand region). The use of neural networks for color division, then the performance of morphological operations and polygonal approximations, as a method to discrete hand area from related and eliminate noise, showed excellent results. This step is central because it removes image objects that are not related to the organisation method, so that the artificial neural network can extract greatest related gestures.

REFERENCES

Ali A., Alani Georgina Cosma Aboozar Taher khani T.M Mc Ginnity. 2018. Hand gesture recognition using an adapted convolution neural network with data augmentation. 4th International Conference on

- Information Management (ICIM) Year: 2018 ISBN: 978-1-5386-6147-5 DOI: 10.1109/ IEEE Oxford, UK
- Bagdanov A. D., Del Bimbo A., Seidenari L., and Usai L., 2012. Real-time hand status recognition from RGB-D imagery," in Proceedings of the 21st International Conference on Pattern Recognition (ICPR '12), 2456–2459.
- Choi J., Park H., and Park J.-I., 2011. Hand shape recognition using distance transform and shape decomposition, in Proceedings of the 18th IEEE International Conference on Image Processing (ICIP '11), 3605–3608.
- Dardas, N. H. and Georganas, N. D. 2011, Real-time hand gesture detection and recognition using bag-of-features and support vector machine techniques, IEEE Transactions on Instrumentation and Measurement, 60(11), 3592–3607.
- Elmezain M., Al-Hamadi A., and Michaelis B., 2010. A robust method for hand gesture segmentation and recognition using forward spotting scheme in conditional random fields," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), 3850–3853.
- Eshitha K.V, oniya Jose. 2018. Hand Gesture Recognition Using Artificial Neural Network" 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET) ISBN: 978-1-5386-0576-9 DOI: 10.1109/ IEEE Kottayam, India.
- Feng X., Qun Song Qingfang Guo Duo Liu Zhanfeng Zhao Yinan Zhao. 2019. Hand Gesture Recognition with Ensemble Time-Frequency Signatures Using Enhanced Deep Convolutional Neural Network. 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC) ISBN: 978-1-7281-3248-8. DOI: 10.1109/ IEEE Lanzhou, China.
- Frati V. and Prattichizzo D., 2011. Using Kinect for hand tracking and rendering in wearable haptics," in Proceedings of the IEEE World Haptics Conference (WHC '11), 317–321.
- Harshitha R., Syed I. A., and Srivasthava S., 2013. Hci using hand gesture recognition for digital sand model," in Proceedings of the 2nd IEEE International Conference on Image Information Processing (ICIIP '13), 453–457.
- Kabir R, Ahmed N, Roy N, Islam M.R. 2019. A Novel Dynamic Hand Gesture and Movement Trajectory Recognition model for Non-Touch HRI Interface. 2019 IEEE Eurasia Conference on IOT, Communication and Engineering ISBN: 978-1-7281-2501-5 2019
- Lee C.-S., Chun S. Y., and Park S. W., 2012. Articulated hand configuration and rotation estimation using extended torus manifold embedding, in Proceedings of the 21st International Conference on Pattern Recognition (ICPR '12), 441–444.
- Liang, W., Guixi, L. and Hongyan, D. 2015, Dynamic and combined gestures recognition based on multi-feature fusion in a complex environment, The Journal of China Universities of Posts and Telecommunications, 22(2), 81–88.
- Malgireddy M. R., Corso J. J., Setlur S., Govindaraju V., and Mandalapu D., 2010. A framework for hand gesture recognition and spotting using sub-gesture modeling," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), 3780–3783.
- Meng Z. Y., Pan J.-S., Tseng K.-K., and Zheng W., 2012. Dominant points based hand finger counting for recognition under skin color extraction in hand gesture control system, in Proceedings of the 6th International Conference on Genetic and Evolutionary Computing (ICGEC '12), 364–367.
- Muralidhar P. Amartya Saha Prashanth Sateesh. 2019. Customizable Dynamic Hand Gesture recognition System for Motor Impaired people using Siamese neural network" 2019 International Conference of Artificial Intelligence and Information Technology (ICAIIIT) ISBN: 978-1-5386-8448-1 DOI: 10.1109/ IEEE Yogyakarta, Indonesia.
- Panwar M., 2012. Hand gesture recognition based on shape parameters, in Proceedings of the International Conference on Computing, Communication and Applications (ICCCA '12), 1–6.
- Park S., Yu S., Kim J., Kim S., and Lee S., 2012. 3D hand tracking using Kalman filter in depth space," Eurasip Journal on Advances in Signal Processing, 1, article 36.
- Pugeault and R. Bowden, 2011. Spelling it out: real-time ASL fingerspelling recognition, in Proceedings of the IEEE International Conference on Computer Vision Workshops (ICCV '11), 1114–1119.
- Raheja J. L., Chaudhary A., and Singal K., 2011. Tracking of fingertips and centers of palm using KINECT, in Proceedings of the 2nd International Conference on Computational Intelligence, Modelling and Simulation (CIMSIm '11), 248–252.
- Rokade, R. S. and Doye, D. D. 2014, Spelled sign word recognition using key frame, IET Image Processing, 9(5), 381–388.
- Sheng R., Zhang Z. 2019. A hand gesture recognition using single-channel electrodes based on artificial neural network. 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC) Year: 2019 ISBN: 978-1-5386-8178-7 DOI: 10.1109/ IEEE Chongqing, China.
- Suryanarayan P., Subramanian A., and Mandalapu D., 2010. Dynamic hand pose recognition using depth data," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), 3105–3108.
- Tan T.-D. and Guo Z.-M., 2011. Research of hand positioning and gesture recognition based on binocular vision, in Proceedings of the IEEE International Symposium on Virtual Reality Innovations (ISVRI '11), 311–315.
- Uebersax D., Gall J., Van den Bergh M., and Van Gool L., 2011. Real-time sign language letter and word recognition from depth data, in Proceedings of the IEEE International Conference on Computer Vision Workshops (ICCV '11), 383–390.
- Wang Y., Yang C., Wu X., Xu S., and Li H., 2012. Kinect based dynamic hand gesture recognition algorithm research, in Proceedings of the 4th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC '12), 274–279.
- Wickerroth D., Benölken P., and Lang U., 2009. Markerless gesture based interaction for design review scenarios, in Proceedings of the 2nd International Conference on the Applications of Digital Information and Web Technologies (ICADIWT '09), 682–687.
- Yan, R. R., Tee, K. P. K., Chua, Y. Y., Li, H. H. and Tang, H. H. 2012, Gesture recognition based on loyalist attractor networks with application to robot control IEEE Computational Intelligence Magazine, 7(1), 64–74.
- Yang R., Sarkar S., and Loeding B., 2010. Handling movement epenthesis and hand segmentation ambiguities in continuous sign language recognition using nested dynamic programming, IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(3), 462–477.
- Zafrulla Z., Brashear H., Starner T., Hamilton H., and Presti P., 2011. American Sign Language recognition with the kinect, in Proceedings of the 13th ACM International Conference on Multimodal Interfaces (ICMI '11), 279–286.