HAND GESTURE RECOGNITION SYSTEM USING MATLAB

Mr. M. Maharaja[1], Ajay V[2], Jagadheeshkumar M[3], Bharathmagan M[4]

[1]Assitant Professor, [2,3,4]UG Scholars, Department of Electronics and Communication Engineering, Adhiyamaan College of Engineering , M.G.R Nagar, Hosur, India.

maharaja.me@gmail.com[1],teejayajay98320@gmail.com[2],jagadhoni4@gmail.com[3],maganbharath@gmail.com[4]

Abstract—*To extract features and reduce its dimension. To reduce the dimension of the feature vector to classify the different hand gestures hand motion acknowledgment has broad application in virtual reality sign language recognition and computer games.The immediate interface of hand motion gives us another approach to speaking with the virtual climate.*

Key Words: **CNN Algorithm, Human-Computer Interface, Gesture recognition system .**

1.INTRODUCTION

Hand motion acknowledgment is vital for human-PC communication (HCI), on account of its broad applications in computer generated simulation and gesture based communication acknowledgment. Regardless of bunches of past work, conventional vision-based hand motion acknowledgment techniques are still a long way from acceptable for some genuine applications. The nature of the caught pictures is touchy to lighting conditions and jumbled foundations, in view of the limits of the optical sensors. Accordingly, it is by and large not ready to recognize just as track the hands powerfully. This to a great extent influences the presentation of hand signal acknowledgment. A viable method to make hand signal acknowledgment more vigorous is to utilize various sensors to catch the hand motion and movement, e.g., through the information glove.In contrast to optical sensors, such sensors are for the most part more solid and are likewise not influenced by lighting conditions or jumbled foundations. Nonetheless, as the client needs to wear an information glove which here and there requires adjustment, it not exclusively is awkward for the client yet in addition may frustrate.

2.RELATED WORK

Customarily, dynamic hand motion acknowledgment frameworks use strategies to extricate hand tailored highlights followed by an arrangement displaying procedure, for example, a secret Markov model (HMM). However, the recent success of learning techniques in image classification, object recognition, speech recognition, and human activity recognition has encouraged many researchers to exploit them for hand gesture recognition. For example, convolutional neural networks (CNN) have been widely used for learning visual features in computer vision.Then again, a 3D convolutional neural organization (3DCNN) has been utilized for video displaying, which is an all-encompassing rendition of standard CNNs that utilizes spatiotemporal channels.This design has been investigated beforehand in a few video examination fields for spatiotemporal element portrayal. The main attribute of 3DCNN is its capacity to straightforwardly make various leveled portrayals of spatiotemporal information.However, it requires more parameters than 2DCNN, which is one of its disadvantages. Moreover, 3DCNN has an additional kernel dimension, which makes it harder to train. Hence, instead of training a 3DCNN from scratch, using domain adaptation on pre trained instances is preferred. In a previous hand gesture recognition work, we implemented a variation of the C3D architecture and used knowledge transfer from human action recognition to hand gesture recognition. The C3D architecture comprises eight convolutional layers, five pooling layers, and two fully connected (FC) layers. However, even though we obtained encouraging results in that work, we noticed that the direct application of 3DCNN for hand gesture modeling has two main drawbacks. Firstly, 3DCNN modeling is not robust enough to capture the long-term temporal dependence of the hand gesture signal. Secondly, modeling the hand gesture signal in a video should be slightly different than other video-based analysis for human activity recognition or event recognition in general. For the latter case, the whole scene and maybe multiple interacting objects in the frame are involved discriminative descriptors for the overall recognition. In contrast, the discriminative features in hand gesture recognition are located mainly in the fingers' configuration, the hand's orientation, and the hand's relative position to the body. In other words.

3. PROPOSED SYSTEM

Specialists have discovered assortment of approaches to collaboration with machines like providing order by voice console, contact screen, joystick and soon. Loads of exploration has been accomplished for the discovery and acknowledgment of hand signals. Since Hand signals have been the most common correspondence medium among person, so this permits human PC association in numerous hardware papers.This examination field has accomplished a great deal of consideration because of its applications and handiness in intuitive human-machine communication and virtual conditions. Such gadgets have gotten comfortable yet it restricts the speed of the correspondence between the clients and the PCs a ton of current works identified with hand signal interfacing procedures has been utilized in AI.

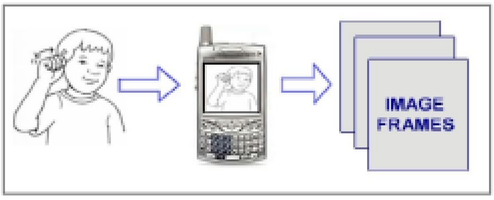

Fig -1: Image frames

3.1 CONVOLUTIONAL LAYERS

The complete building block of CNN is convolutional layer. The layer consists of learnable filters and these filters have small reception fields. In each forward pass, it will produce a two-dimensional map of corresponding filter by calculating the dot product between input and entries of filter. By this, the network will learn about the filters which are activated when specific feature at specific spatial position occurs. The depth dimension with activation maps of each filter will form the full output volume of convolutional layer.

3.2 POOLING LAYERS

Pooling is a non-linear down sampling. To implement the pooling layer, the most common non-linear function. The max pooling layer separates the input picture into congregation of non-overlapping squares and the layer will output the maximum for each sub region. If a feature is identified, then this helps in finding the rough location relative to other features. The intermediate representation's dimensionality will be reduced by max pooling. Pooling layers are injected in between convolutional layers.

3.3 FULLY CONNECTED LAYERS

The fully linked layers do the high-level reasoning of a neural network. This layer connects all the neurons of the previous layers (convolutional or pooling or Connected). The activation function is estimated by a matrix multiplication, and then a bias offset will be added.

4. METHODOLOGY

Five different gestures are considered corresponding to five different English alphabets in Indian Sign Language. The alphabets used are Y, V, L, S, I. Firstly; each gesture/signature is segmented to extract the hand. The hand is the closest object to the camera. This property used to segment the hand in the image by considering a certain depth interval. The result is a binary segmented image with black segmented hand in white background. The contour of the segmented hand is found and a maximum inscribed circle is found for the corresponding contour. The next step is time-series curve representation of the signature.The time-arrangement bend records the general distance between each form vertex and a middle point.

Horizontal axis denotes the normalized angle between each contour vertex and the initial point with respect to the center point. The normalization is done by 360◦ .

5. EXPERIMENT RESULT

At the heart of MATLAB is a new language you must learn before you can fully exploit its power. You can learn the basics of MATLAB quickly, and mastery comes shortly after. You will be rewarded with high productivity, high-creativity computing power

Fig -2: Input Image

FIG -3: Segmented Image

6. CONCULSION

Many breakthroughs have been made in the field of artificial intelligence, machine learning and computer vision.They have monstrously contributed by they way we see things around us and improve the manner by which we apply their methods in our regular daily existences. Numerous explores have been led on sign motion acknowledgment utilizing various procedures like ANN, LSTM and 3D CNN. Notwithstanding, a large portion of them require additional figuring power. Then again, our exploration paper requires low registering force and gives an astounding precision of above 90%.In our exploration, we proposed to standardize and rescale our pictures to 64 pixels to remove highlights (parallel pixels) and make the framework more strong. We use CNN to arrange the 10 in sequential order American sign signals precision of 98% which is superior to other related work expressed in this paper.

REFERENCES

[1] ZhenyuanZhang; Zengshan Tian;Ying Zhang;Mu Zhou; Wang, Year:2019, "u-DeepHand: FMCW Radar-Based Unsupervised Hand Gesture Feature Learning Using Deep Convolutional Auto-Encoder Network", IEEE Sensors Journal, vol.19, no.16, pp. 6811 – 6821.

[2] Lars Ohlsson Fhager Sebastian Heunisch; Hannes Dahlberg;Anton Evertsson;Lars-Erik Wernersson, Year:2019, "Pulsed Millimeter Wave Radar for Hand Gesture Sensing and Classification", IEEE Sensors Letters, vol.3, no.12, pp.1-4.

[3] Saleh Aly;Walaa Aly, Year:2020, "DeepArSLR: A Novel Signer-Independent Deep Learning Framework for Isolated Arabic Sign Language Gestures Recognition", IEEE Access, vol.8, pp. 83199 – 83212.

[4] Muneer Al-Hammadi; Ghulam Muhammad;Wadood Abdul;MansourAlsulaiman;Mohammed A. Bencherif;Tareq S. Alrayes;Hassan Mathkour;Mohamed Amine Mekhtiche, Year:2020, "Deep Learning-Based Approach for Sign Language Gesture Recognition With Efficient Hand Gesture Representation", IEEE Access, vol.8, pp. 192527 – 192542.

[5] Bin Fangfang Helsingin Wang;Yongjiang Wu;Hao Wang;Sihua Yi;Wenyu Liu, Year:2017, "Depth-Projection-Map-Based Bag of Contour Fragments for Robust Hand Gesture Recognition", IEEE Transactions on Human-Machine Systems, vol.47, no.4, pp. 511 – 523.

[6] Gang Li;Rui Zhang;Matthew Ritchie;Hugh Griffiths, Year:2018, "Sparsity-Driven Micro-Doppler Feature Extraction for Dynamic Hand Gesture Recognition", IEEE Transactions on Aerospace and Electronic Systems, vol.54, no.2, pp. 655 – 665.

[7] Feifei Zhou;Xiangyu Li;Zhihua Wang, Year:2020, "Efficient High Cross-User Recognition Rate Ultrasonic Hand Gesture Recognition System", IEEE Sensors Journal, vol.20, no.22, pp. 13501 – 13510.

[8] Wei Fang;Yewen Ding;Feihong Zhang;Jack Sheng, Year:2019, "Gesture Recognition Based on CNN and DCGAN for Calculation and Text Output", IEEE Access, vol.7, pp. 28230 – 28237.

BIOGRAPHY:

Mr. M. Maharaja,
Assistant Professor,
Engineering Department,
Adhiyamaan College of Engineering,
Anna University.