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Hand Gesture Digit Recognition using Machine Learning with Image Processing

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Abstract: In this paper a novel method for hand gesture recognition system for two digit classification through webcam is proposed. The benefit of sign language is to overcome a communication barrier gap among people who have speech as well as hearing problems. Actually sign language is a combination of gestures as well as postures. Gestures uses hand for making signs with hand or without an object which is the natural way of communication. Sing language system helped disable people to express their emotions without the aid of an interpreter. The basic idea of this system is to identify gestures from digital images or image capturing electronic devices and convert it into text. Gesture based communication is very complex due to variation in color, size and shape of the hand of individuals. Different methods for gesture recognition are data glove-based method, motion sensors connected to the hand. These sensors collect the information about the position and motion of the hand and is costly. To overcome the limitations of data glove-relied methods, a vision-based methodology should be developed which should be fast as well as reliable. The proposed system combined the learning capabilities of machine learning with the live feed of image processing to solve the recognition problem.

Keywords: Hand gesture, Segmentation, Image processing, Postures, Machin learning

I. INTRODUCTION

This document is a template. For questions on paper guidelines, please contact us via e-mail. In modern time sign recognition is usually processed in three fundamental steps.

- A. Region of interest or segmentation,
- B. Feature extraction and
- C. Classification

Segmentation process is utilized for separating out hand part with clear boundaries. Different algorithms have high efficiency and are dependent on either particular uniform light conditions should as well as plane background. These two conditions should be essential as well as hand position must be in centre of the image [1].

Feature extraction process is used to simplify the amount of resources needed to explain a large set of data accurately. The differentiation between gestured and non gestured frames is very important before feature extraction. In making sequence of static hand gestures, the hand makes intermediate movements between the two gestures. Without knowing the gesture boundaries, reference patterns have to be matched with all possible segments of input signals. In case of dynamic gesture recognition, video sequence is the input to the system. Every time hand pose and hand movement speed may vary. Speed of signing affects on recognition efficiency [2]. Classification is utilized to find the accurate results after matching or correlating the information present in the target image with the trained image samples. This process is used to find best match for the target image.

Hand gesture is a very effective way of expressing thoughts as due to it simple nature that can effectively fulfill the basic requirements of interaction with people. Hand gesture also provides an attractive way to cumbersome interface devices for human computer interaction (HCI). Sign language usually contains different gestures each of which must be associated with a specific thought interpretation [3]. The benefit of sign language is to overcome a communication barrier gap among people who have speech as well as hearing problems. Actually sign language is a combination of gestures as well as postures. Gestures uses hand for making signs with hand or without an object which is the natural way of communication. It has worldwide application in electronic gadgets, robotics and augmented reality and many more. Sign language system helped disable people to express their emotions without the aid of an interpreter. The basic idea of this system is to identify gestures from images or image capturing electronic devices and convert it into text. Gesture based communication is very complex due to variation in color, size and shape of the hand of individuals [4].



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Fig. 1. Hand gesture and threshold image [1]

Different methods for gesture recognition are data glove-based method, motion sensors are connected to the hand. These sensors collect the information about the position and motion of the hand. The sensor-based method requires an appropriate equipment setup. It may interfere with the natural movement of the hand and is costly. To overcome the constraints of data glove-based method, a vision-based method is developed. Vision-based method employs cameras to capture the hand gestures. Vision-based techniques are classified as 3-D hand model-based and appearances-based methods. 3-D hand model based method uses four different types of cameras such as stereo, monocular, angle eye, time of flight, infrared etc. to generate 3-D hand model for gesture recognition. Noisy gestures refer to valid gestures with some additive noise, present due to device flaws, user's inexperience with the recognition system or user's temporary or permanent behavioral characteristics, such as anxiety, trembling hand, or movement limitations [5].

II. LITERATURE REVIEW

S. R. Kalbhor et al. in 2018 [1] proposed hand gesture recognition system was implemented for recognition of 0-9 digits. In this paper, authors compared the performance of two methods. First one was the contour-SVM based method and second was Convolutional Neural Network (CNN) method under variable circumstances as rotation and scaling of image with a constant background. The proposed techniques were operated on three world class databases-SLD, ASL and ASL-FS. In the contour-based technique authors found that the contour and draw convex hull. Gestures were recognized according to the length and angle of convex hull and SVM was utilized for classification purpose. CNN relied technique utilized five convolutional layers for classifying the digit data. Authors had utilized more than 10,000 digital images from the database for 1-10 digits to perform hand gesture recognition. This database was originally collected from a Creative Senz3D camera having resolution 320x240. Authors showed that proposed algorithm achieved accuracy near to 69% for contour-SVM and 98.31% accuracy for CNN based approach.

Y. Yao et al. in (2015) [6] proposed a technique which was relied on a novel classifier weighting scheme to get the recognition of different gestures in uncontrolled environments. The technique was capable of generating good performance in spite of occurrence of different challenges. Two databases were utilized to find the effectiveness of the proposed method which was the Palm Graffiti Digits and the other was the Warwick Hand Gesture Database. The outcome of the proposed technique showed that the proposed method could deal with the different conditions rising from the uncontrolled environments without any initial knowledge and increased the performance of the classifier. The prime benefits of the proposed method were that it was capable of performing fast HGR and HGS in uncontrolled environments with held of two dimensional camera and other was the capability of enhancing the performance of the initial classifier on HGR and HGS in different conditions. At last authors got 92 % accuracy in comparison to other techniques.

O. De et al. in 2016 [7] presented an idea of developing a gentle framework utilizing computer vision for hand gesture relied sign language recognition from real-time video stream. The proposed system identified palm of the hand in live video stream and was relied on color of the skin with the help of background subtraction of the image processing technique. This scheme had benefit in comparison to old techniques of utilizing gloves or markers as interface. Authors had also proposed an iterative polygonal shaped approximation algorithm in fusion with a special chain-coding technique to match feature of shape-similarity. This proposed framework considered digits as important symbols of sign language. The system quite successfully recognized hand gestures in correspondence to different numerical digits with relevant acceptable accuracy. Authors got 82 % accuracy in comparison to other methods.



R. R. Shinde et al. in 2016 [8] proposed a dynamic hand gesture recognition for digits. The proposed technique has three fold novel contributions. First of all it tried to find the flow of hand and in the second time it tried to recognize digits and in the end it displayed the gesture. Authors tried to work on 11 to 20 (digits) gestures. Authors found that the spatiotemporal volume was not always help to find the flow of hand movement. Proposed algorithm showed recognition efficiency of 94% for dynamic gestures. Further it was found that the time complexity of the proposed method was less as compared to other methods.

Z. Yang et al. in 2012 [9] introduced an HMM relied technique to recognize different complex gestures of single hand. Gesture images were gained by a normal web camera. Skin color was utilized to segment hand area from the digital image to form a hand image sequence. Authors put forward a state relied spotting algorithm for splitting random progressive gestures. Then feature extraction was executed on individual gesture. Features utilized in the system contain different random variables like hand position, velocity, size, as well as shape. Authors raised a data aligning algorithm for aligning feature vector sequences for training. Then an HMM was trained alone for each gesture. The recognition outcomes demonstrated that proposed technique was very effective as well as accurate. The total recognition rate was found to be nearly 96.67%.

III.PROBLEM FORMULATION AND METHODOLOGY

The benefit of sign language is to overcome a communication barrier gap among people who have speech as well as hearing problems. Actually sign language is a combination of gestures as well as postures. Gestures uses hand for making signs with hand or without an object which is the natural way of communication.

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Different methods for gesture recognition are data glove-based method, motion sensors are connected to the hand. These sensors collect the information about the position and motion of the hand. The sensor-based method requires an appropriate equipment setup. It may interfere with the natural movement of the hand and is costly. To overcome the constraints of data glove-based method, a vision-based method should be developed which should be fast as well as reliable.

A. Objectives

This research work will be focused to achieve the following objectives:-

- 1) To design, study and implement a two digit sign recognition framework.
- 2) The framework should be fast and reliable.
- 3) The proposed framework should be implemented on different datasets.
- 4) Main focus on improving the speed of digit recognition system with noise present or not.
- 5) To learn from the design process, identify and solve possible bottlenecks in detection and recognize hand gestures digits which contributes to the overall recognition quality.

B. Methodology

The following steps will be performed to complete this research work:-

- 1) Create a system that detects the hand of the individual and then the fingers of the system.
- 2) Train the system as it detects whether it is left hand or right hand.
- 3) Perform opening and closing morphological operations to detect the shape of the gesture.
- 4) Create database or use some recognized database for gesture matching.
- 5) Map the result of recognition with the database.
- 6) Test the authenticity or reliability of the system with conducting different operations.

C. Proposed Algorithm

The proposed algorithm includes training as well as detection of the segmented image. The specific process is as follows:

- 1) Detect left as well as right hand of the individual
- 2) Train model for digits 1 to 5.
- 3) Perform opening and closing operations to detect boundary of the samples.
- 4) Extract features from the trained images.
- 5) Classify the target image with segmentation technique to correlate the trained data.





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Fig. 2 Flowchart of proposed algorithm





Fig. 4 Left and right hand image of sample



Fig. 6 Segmented image of original hands

Fig. 5 Extracted image of both hands



Fig. 7 Classified image of both hands



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Fig. 8 Final output displayed with value '55'



Fig. 9 Left and right hand image of sample



Fig. 11 Extracted image of left hand



Fig. 10 Extracted image of left hand



Fig. 12 Classified image of both hands



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Fig. 13 Final output displayed with value '44'

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		Hand	Hand	Hand	Hand		system	
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2	2	1,3	4,1	1,3	4,1,3	25	94	
3	2	1,4	2,4	1,4,5	2,4	25	92	
4	2	1,5	2,3.4	1,5	2,3,4	25	90	
5	2	2,5	3,4	2,3,5	3,4	25	88	
6	2	2.4	1,2	2,4	1,2	25	92	
7	2	2,3	1,3,5	2,3,4	1,3,5	25	93	
8	2	3,1	3,4,5	3,4,1	3,4,5	25	90	
9	2	3,4	1,2	3,4,5	1,2,3	25	95	
10	2	5,2	1,3,5	5,2,3	1,3,5	25	85	

Table I: Overall performance matrices of the sign recognize system

After performing 250 rounds of tests for digits 1 to 5 by both left and right hand the overall accuracy of the system is found to be 91.5% which is very good for the proposed system.

V. CONCLUSIONS

From the results it is cleared that proposed algorithm tries to find the exact boundary of both left as well as right hand segmented images and then tries to classify the segmented images with the trained images which is dependent on the amount of correlation data among the both images. The outcomes of the proposed technique have very smooth and refined edges in case of both left as well as right hand and technique does not remove any detail present in the image. So the proposed technique shows good results and it proves the worthiness of the system.

In the future work digits from 6 to 9 and 0 could be trained to get the other combination of results. Also the system accuracy can be increased by using the other trained data by different people of different ages.

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