

Multiple Features based Recognition of Static American Sign Language Alphabets

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ABSTRACT

Communication with the hearing impaired people without the help of interpreter is a big challenge for common people. Thus efficient computer based recognition of sign language is an important research problem. Till now numbers of techniques are being developed. This article explains a novel method to recognize the 24 static image based alphabets A to Z (excluding dynamic alphabets J and Z) of American Sign Language (ASL) using two different features. This method extracts the feature vector of the images based on the simple method of orientation histogram along with the statistical parameters. Further neural network is used for the classification of these alphabets. This method is qualified to provide an average recognition rate of 93.36 percent.

Keywords

American Sign Language, ASL alphabets, Neural Network, Static Hand Gesture Recognition, Orientation Histogram, Statistical Measures

1. INTRODUCTION

Computers are used by many people in their day to day life for all activities. Special input and output devices have been designed over the years with the purpose of easing the communication between computers and humans, the two most known are the keyboard and mouse [1]. The idea is to make computers understand human language and develop a user friendly human computer interfaces (HCI). Making a computer understand speech, facial expressions and human gestures are some steps towards it. Gestures are the non-verbally exchanged information. A person can perform innumerable gestures at a time. Since human gestures are perceived through vision, it is a subject of great interest for computer vision researchers. Coding of these gestures into machine language demands a complex programming algorithm.

Gestures are classified into two distinctive categories: dynamic and static [1]. A dynamic gesture is intended to change over a period of time, whereas a static gesture is observed at an instance of time. Dynamic gestures are considered as consecutive sequences of hand or head or body postures in sequence of time frames. A waving hand means goodbye, is an example of a dynamic gesture and the stop sign is an example of static gesture. To understand a full message, it is necessary to interpret all the static and dynamic gestures over a period of time. This complex process is called gesture recognition. Gesture recognition is the process of recognizing and interpreting a stream continuous sequential gesture from the given set of input data. Dynamic gesture recognition is accomplished using Hidden Markov Models (HMMs), Dynamic Time Warping, Bayesian networks or other pattern recognition methods. Static gesture (or pose gesture)

recognition can be accomplished by using template matching, eigen spaces or PCA (Principal Component Analysis), Elastic Graph Matching, neural network or other standard pattern recognition techniques. Template matching techniques are actually the pattern matching approaches. It is possible to find out the most likely hand postures from an image by computing the correlation coefficient or minimum distance metrics with template images.

Gesture recognition has significant application in sign language recognition. Sign languages are the most raw and natural form of languages that could be dated back to as early as the advent of the human civilization, when the first theories of sign languages appeared in history. Sign languages are being used extensively in international signs used by deaf and dumb, in the world of sports, for religious practices and also at work places. Hearing impaired people have over the years developed a gestural language where all defined gestures have an assigned meaning. The language allows them to communicate with each other and the world they live in. Fig. 1 shows the different gestures in an American Sign Language for the alphabets A to Z.

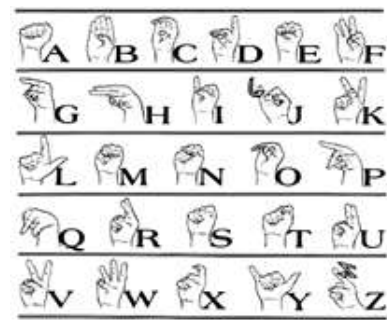


Fig. 1: Gestures in American Sign Language.

2. RELATED WORK

In sign language recognition, it is desirable to use a shape representation technique that will sufficiently describe the shape of the hand while also being capable of fast computations, enabling recognition to be done in real-time. It is also desirable for the technique to be invariant to translation, rotation, and scaling. In addition, a method that will allow for easy matching would be beneficial. Gesture recognition was first proposed by Myron W. Krueger as a new form of interaction between human and computer in the middle of a seventies [2]. Currently, there are several available techniques that are applicable for hand gesture recognition. Zimmerman [3] developed a VPL data glove that is linked to the computer to recognize signs. The glove can measure the bending of fingers, the position and orientation of

the hand in 3-D space. In vision-based gesture recognition, hand-shape segmentation is one of the toughest problems under a dynamic environment. It can be simplified by using visual markings on the hands. Some researchers have implemented sign language and pointing gesture recognition based on different marking modes [4]. Arpita Ray Sarkar[5] et al reviews the work carried out in last twenty years and presents brief comparison to analyze the difficulties encountered by these systems, as well as the limitation. The desired characteristics of a robust and efficient hand gesture recognition system have been described. Klimis Symeonidis [6] used an orientation histogram of the image to develop a simple and a fast algorithm to extract features from the static image for comparison and recognize some of the alphabets of a static ASL using neural network. Becky Sue Parton [7] discusses various projects involving sign language and the potential impact these endeavors will have on deaf education and communities at large. He also discusses the use of artificial intelligence in the field robotics, virtual reality, computer vision, neural networks, Virtual Reality Modelling Language (VRML), three-dimensional (3D) animation, natural language processing (NLP), and an intelligent computer aided instruction (ICAI), for sign language manipulation. Jonathan C. Rupe [8] developed the system to

identify hand shapes commonly found in American Sign Language using the region-based Generic Fourier Descriptor. Other approaches such as; local linear embedding, Neural Network shape fitting, object based key frame selection, and Haar wavelet representations have been presented in [9], [10-12]. Asha Thalange et al [13] proposes an ASL Number Recognition Using Open-finger Distance Feature Measurement Technique. S. Nagarajan [14] et al proposes a static hand gesture recognition system for American Sign Language using Edge Oriented Histogram (EOH) features and multiclass SVM. Rafiqul Zaman Khan [15] discusses key issues of hand gesture recognition system with challenges of gesture system. He also present review of methods of recent postures and gestures recognition system. Summary of research results of hand gesture methods, databases, and comparison between main gesture recognition phases are also given. Advantages and drawbacks of the discussed systems are explained.

3. SYSTEM DESCRIPTION

The block diagram of the proposed system is as shown in the fig. 2. Here the ASL alphabets A to Z are considered excluding the alphabet J and Z as the sign for these alphabets is not static.

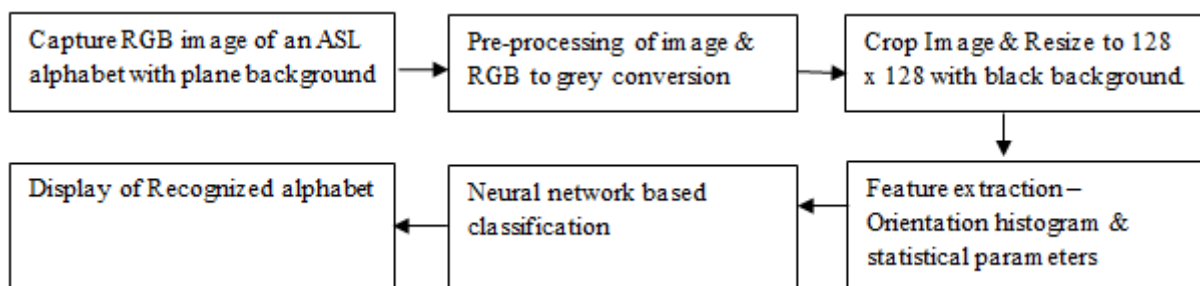


Fig. 2: System Block Diagram

The whole system functioning is divided into four main modules namely:

- Image capture and Pre-processing
- Image cropping and resize
- Feature extraction
- Classification

3.1 Image capture and Pre-processing:

The color image of the sign of an ASL alphabet with a plane black background is captured by a 5 megapixel web-camera concentrating on the palm of the hand. The plane background is used for simplicity of processing. The extracted image of ASL gesture from the signer is first pre-processed to enhance the image's quality. For this low pass filtering and median filtering is applied to the input image. Further, the color image is converted to grey scale image of size 256 x 420 pixels. The dataset is created by us. The total of 720 images are captured for training, which consists of 30 images per alphabet sign (A to Z except J and Z), by a single signer, along with a separate set of, a total of 823 images of all alphabets, for testing. The database consists of the images which are obtained with varying scale and contains rotated samples between +45 and -45 degree in order to make system robust.

3.2 Image cropping and resize:

In order to make the image scale invariant, the pre-processed image is cropped to segment the background and concentrate only on the palm.

To obtain this, first the grey scale image is converted to binary image with a black background and white hand. Further median filtering and morphological operations are applied to remove noise. Image thinning is applied to some extent to a binary image in order to get clear separation among the edges and enhance the shape. The extent of thinning is limited so that the image is not totally converted to a skeleton. Considering the extreme points of the hand in all the four directions, the segmented image of the hand from the background is obtained. A new image is obtained by filling the respective white pixels of the segmented image by the grey values from its original grey image. This segmented grey image is further resized to 128x128 pixels. Thus, making the sign image scale independent.

3.3 Feature extraction:

In order to enhance the recognition rate, this method proposes to extract two different features of the image which together acts as a feature vector for classification. The cropped resized image is further used to extract features such as orientation histogram and statistical parameters of the image.

Orientation histograms are easier and faster for computation. They are robust against illumination changes. For the orientation histogram, the gradients in x direction are obtained by convolving the image by $x = [0 \ -1 \ 1]$ and in y direction by $y = [0 \ -1 \ 1]^T$ resulting into two gradient images dx and dy. Gradient direction and magnitude is further computed as

$$\text{gradient direction} = \text{atan}(dx, dy) \quad \text{---(1)}$$

$$\text{gradient magnitude} = \sqrt{(dx^2 + dy^2)} \quad \text{---(2)}$$

Further converting the matrix with the radian values to degrees, scanning is done to get the count of degrees in the different histogram bins. Here each bin is of 10^0 wide so a total of 18 bins are formed. This vector of count of degrees acts as the part of the feature vector used for training.

In order to extract the statistical measures of the image the grey scale 2D image is converted to 1D. Here six parameters

such as mean, standard deviation, variance, coefficient of variance, range, root mean square of successive difference are calculated. These further are added to the feature vector to get a final feature vector of length 24.

3.4 Classification:

Multi-layered feed forward back-propagation Neural Network based classification engine is used here. Initially, the network is trained with feature vectors obtained from training set consisting of 30 images of each ASL alphabet obtained from a single user. The feature vector obtained from the actual test images is applied to this trained network for classification or recognition of an ASL alphabet sign. Further, the detected alphabet is displayed in text form.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

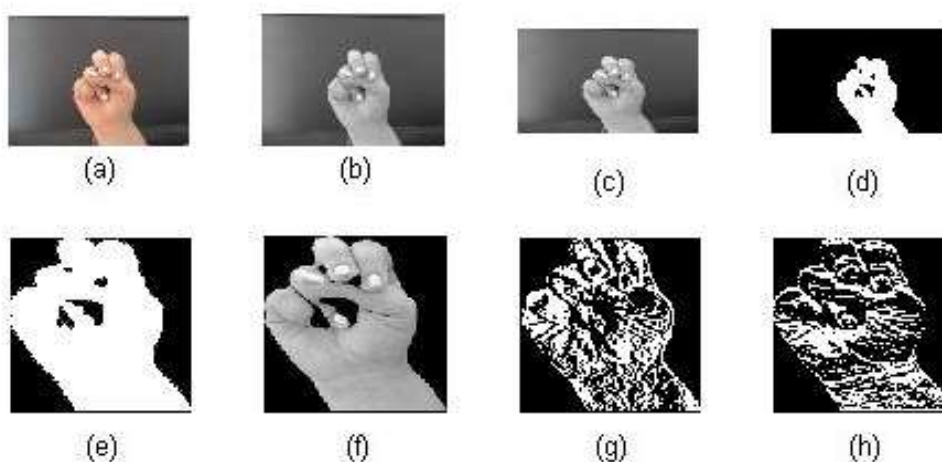


Fig. 3: Different processing stages of sign of ASL alphabet N

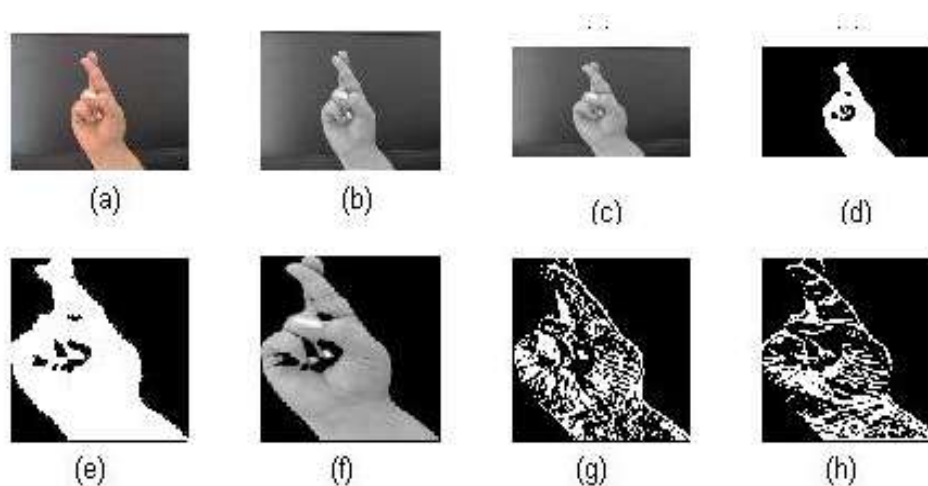


Fig. 4: Different processing stages of sign of ASL alphabet R

Fig. 3 shows the different processing stages of sign of ASL alphabet N. Fig. 3.a shows the captured RGB image. Fig. 3.b shows the RGB to Grey scale image. Fig. 3.c shows the resized 256x420 grey scale image. Fig. 3.d is filtered and morphologically processed binary image. Fig. 3.e and 3.f

shows the cropped binary and grey scale image. Fig. 3.g and 3.h shows the gradient image dx and dy in x and y direction for the cropped grey scale image. Similarly, Fig. 4 shows the different processing stages of sign of ASL alphabet R.

TABLE I: Classification Result Of Test Images For ASL Alphabets A To Z Using Orientation Histogram Features Only.

		I/P test images																									
O/P		A	b	c	d	e	f	g	h	I	k	l	m	n	o	p	Q	r	s	t	u	v	w	x	y		
d e t e c t e d	a	27	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	5	0	0	0	0	0		
	b	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	c	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	d	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	e	0	0	0	0	26	0	0	0	6	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0		
	f	1	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	g	0	0	0	0	0	0	28	4	0	0	0	0	0	0	1	0	0	0	0	0	0	8	0	0		
	h	0	0	0	0	0	0	0	28	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0		
	i	0	0	0	0	0	0	0	0	23	0	0	1	1	4	0	0	0	0	1	0	0	0	0	0		
	k	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	l	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0		
	m	0	0	0	0	1	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0		
	n	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0		
	o	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0		
	p	0	0	0	0	0	0	0	0	0	0	0	1	0	0	32	0	0	0	0	0	0	0	0	0		
	q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0		
	r	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	1	0	3	0		
	s	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0		
	t	2	0	0	0	0	0	0	0	2	0	0	0	1	1	0	0	0	0	30	0	0	0	0	0		
	u	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	29	0	1	0	0		
v	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	5	30	12	9	0			
w	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0			
x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	47	0			
y	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30			
detected		27	29	33	34	26	32	28	28	23	40	35	49	23	27	32	30	25	36	30	29	30	11	47	30		
Total Image		31	29	33	34	29	32	29	32	32	40	37	52	27	33	33	30	30	36	36	34	31	34	59	30		
% of recognition		87	100	100	100	90	100	97	88	72	100	95	94	85	82	97	100	83	100	83	85	97	32	80	100		
Average%		89.64																									

TABLE II: Classification Result Of Test Images For ASL Alphabets A To Z Using Statistical Measures Only.

		I/P test images																									
O/P		A	b	c	d	e	f	g	h	I	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y		
d e t e c t e d	a	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0		
	b	1	28	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0		
	c	0	0	27	0	1	1	1	0	0	0	0	0	0	0	0	0	16	0	1	13	0	0	0	0		
	d	0	0	0	32	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	e	0	0	0	0	21	0	0	0	2	0	0	0	0	5	0	0	0	0	1	0	0	0	0	0		
	f	5	1	0	0	0	2	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	g	0	0	0	0	0	0	20	0	0	0	3	0	0	0	0	2	0	0	0	0	2	7	0	2		
	h	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	i	0	0	0	0	2	3	0	0	13	0	0	3	0	1	0	0	0	0	3	0	0	0	0	0		
	k	0	0	0	0	0	0	0	16	0	34	9	0	0	0	0	0	0	0	0	0	0	0	0	0		
	l	0	0	0	0	0	0	2	0	0	0	18	0	0	0	0	1	0	0	0	0	0	0	0	0		
	m	0	0	0	0	0	23	0	0	0	0	0	48	0	0	0	0	16	2	0	0	0	0	0	0		
	n	0	0	0	0	0	0	0	0	0	0	0	0	27	3	0	0	0	0	7	0	0	0	0	0		
	o	1	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	1	0	0	0	0	0		
	p	0	0	0	0	0	0	0	2	0	0	0	0	0	0	15	0	0	0	0	0	0	3	8	1		
	q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	1	0	0	0	0	10	0	0		
	r	0	0	4	2	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0		
	s	0	0	0	0	0	3	0	0	6	0	0	1	0	0	0	0	0	17	1	1	0	0	0	0		
	t	3	0	0	0	2	0	0	0	1	0	0	0	0	1	0	0	0	1	14	0	0	1	0	0		
	u	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	2	11	0	0	0	0		
v	0	0	0	0	0	0	0	0	0	0	1	0	0	0	5	0	0	0	0	9	25	1	15	0			
w	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	3	9	0	2			
x	0	0	0	0	0	0	5	9	0	6	6	0	0	0	13	0	0	0	0	0	1	2	36	5			

	y	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	20	
Detected		20	28	27	32	21	2	20	5	13	34	18	48	27	23	15	24	7	17	14	11	25	9	36	20
Total Image		31	29	33	34	29	32	29	32	32	40	37	52	27	33	33	30	30	36	36	34	31	34	59	30
% of recognition		65	97	82	94	72	6	69	16	41	85	49	92	100	79	45	80	23	47	39	32	81	26	61	67
Average %		61.8																							

TABLE III: Classification Result Of Test Images For ASL Alphabets A To Z Using Orientation Histogram And Statistical Measures Taken Together.

		I/P test images																									
		a	b	c	d	e	f	g	h	i	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y		
O/P	a	28	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	
	b	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	c	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	d	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	e	0	0	0	0	28	0	0	0	1	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	
	f	0	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	
	g	0	0	0	0	0	0	29	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	h	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	i	0	0	0	0	1	0	0	0	0	30	0	0	0	0	2	0	0	0	0	1	0	1	1	0	0	
	k	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	l	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	
	m	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	
	n	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	
	o	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	
	p	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	
	q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	
	r	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	
	s	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	36	1	0	0	1	0	0	
	t	2	0	0	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	31	0	0	0	0	0	
	u	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	33	0	0	0	0	
	v	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	13	9	0	
	w	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	16	0	0	
	x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	50	0	
	y	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	2	0	30	
	detected		28	29	33	34	28	32	29	31	30	40	37	47	25	29	33	30	27	36	31	33	26	16	50	30	
	Total Image		31	29	33	34	29	32	29	32	32	40	37	52	27	33	33	30	30	36	36	34	31	34	59	30	
% of recognition		90	100	100	100	97	100	100	97	94	100	100	90	93	88	100	100	90	100	86	97	83	47	85	100		
Average %		93.36																									

Table I, II, III shows the summary of the recognition of total signs of an ASL alphabets A to Z (excluding J and Z), applied to the system, by considering orientation histogram and statistical measures of the image as feature vector. From the result it can be seen that, the system gives lower average recognition rate when only statistical measures are used as feature vector. Also if the orientation histogram of image is used as the feature vector then the recognition rate increased to 89%. But when orientation histogram and statistical measures together are used as a feature vector the recognition rate increased to 93%.

5. CONCLUSION

Compared to glove based or all other complex feature extraction techniques, orientation histogram is a very simple and fast method of feature extraction techniques which is used in hand gesture recognition. When used for ASL alphabets recognition, the average recognition rate is less than 90%. When this feature is combined with the statistical parameters of the image, the average recognition rate increased to 93%.

This shows that multiple features when combined together can form strong feature vector for classification.

6. FUTURE SCOPE

Effect of combination of some other efficient features extracted from image can be used as a feature vector. Also other classification algorithms can be applied to the same feature vector in order to increase the recognition rate.

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