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Visual Interpretation of ASL Finger Spelling using Hough Transform and Support Vector Machine

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Abstract: This paper proposes a vision based automated system for interpretation of American Sign Language (ASL) finger spelling using image processing. A graphical user interface is developed for the hard of hearing community to interact with normal hearing persons through hand gestures in a natural way thereby eliminating the need for an interpreter. This system does not require the user to wear any data gloves or special hardware for recognition of gestures and it provides human-machine interaction only through bare hand. In this research, Hough Transform is employed for feature extraction and gesture modeling and classification is performed through Support Vector Machine (SVM). The finger spelling of alphabets is carried out to form different isolated words. The proposed system is tested on the benchmark Triesch ASL dataset for recognition of individual alphabets and the test results show that this system achieves the overall recognition accuracy of 93.88%.

Keywords: Computer Vision, Hough Transform, Machine Intelligence, Pattern Recognition, Sign Language Recognition, Support Vector Machine**.**

I. INTRODUCTION

Basically, a sign consists of three major components namely gestures made with hands, facial expressions or body postures and the finger spelling where the words are spelt in a non-verbal language. Sign language shortens the time needed for communication through gestures and also allows the possibility of sharing the feelings in a faster way. Developing sign language based applications are extremely beneficial, since certain people in the society are not able to speak and hear. In hand gesture recognition, the hand region alone is detected from the gesture image, and it is analyzed by the computer for interpreting the meaning of the sign. Hand signals assume an essential part in hard of hearing correspondence particularly in American Sign Language. By and large, gesture based communication is an accumulation of motions, hand postures, finger developments and outward appearances of respective alphabets or words. A simple gesture represents the movement of fingers without changing the position and orientation of hand, whereas the complex posture is the movement of fingers, wrist or hand involving the change in position and orientation. Gestures are divided into static gestures and dynamic gestures. Moreover, dynamic gestures with hand motion convey more information than static gestures. In this work, only static gestures are considered for recognition. The main objective of this finger spelling recognition system is to present a simple and efficient mechanism to translate the sign into text. By using Hough transform and Support Vector Machine, the proposed system can visually recognize the static gesture images which represent the alphabets of American Sign Language and interpret them in the form of text. The different stages involved in this research are collection of gesture dataset, edge detection, feature extraction, gesture modeling and recognition.

Fig. 1 ASL Signs

The American Sign Language is selected for recognition in this work since it has its own grammar which is not the same as other sign languages such as British, Persian, Indian or Swedish. It consists of more than 5000 gestures for communicating alphabets/isolated words through finger spelling. The ASL finger spelling has 26 signs to represent the English alphabets (among which only J and Z are dynamic signs) as shown in Fig. 1. In this preparatory exploration, the isolated words which are the blend of the specific ASL letters A,B,C,D,G,H,I,L,V and Y are perceived utilizing Hough Transform and SVM, a supervised machine learning strategy.

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II. RELATED WORK

Several research works have been done so far by the researchers in the field of hand gesture recognition. However, an interesting vision based hand gesture recognition technique has been implemented using PCA and Gabor filters in [1]. Neha Tavari et.al [2] proposed an automated recognition system for Indian Sign Language alphabets and numbers using neural networks, since very few researches have been done so far in Indian Sign Language. Translation of ASL finger spelling to text using image processing is presented in [3]. In this work, ASL alphabets are recognized using pixel matching technique. In paper [4], a robust and efficient system is proposed to recognize 36 static ASL gestures using SIFT features. DCT based feature extraction and minimum Euclidean distance based classification of hand gestures is discussed in [5]. An elaborate survey of hand gesture recognition techniques and key challenges is presented in [6].

A novel method involving point of interest (POI) and track point for real time recognition of sign language using neural networks is introduced in [7]. Some meaningful hand shapes are recognized in [8] by detecting the finger peaks. This system helps the deaf and dumb people to communicate with others without the need of an interpreter. The development of ASL word recognition using neural networks and a probabilistic model is explained in [9], where a cyber glove and a motion tracker are used to extract the gesture data. Static hand gestures for ASL alphabets are recognized in [10] using Back propagation neural network. A scaling, rotation and translation invariant system for static ASL gesture recognition is discussed in [11]. To facilitate the real time conversation between deaf and the normal persons, an accelerometer based translation system is proposed by Jamal Haydar et.al [12]. A neural network based gesture recognition system [13] uses kinetic camera for skeletal tracking. Usage and investigation of an ongoing stereo vision hand tracking framework is given in [14] to perceive British Sign Language (BSL) words.

A real time system which recognizes 26 static ASL hand gestures from complex background is proposed in [15]. Here, gestures are recognized using feature matching technique. Various gesture modeling techniques and classifiers are analysed and compared in [16]. Tamil sign language alphabets are recognized using image processing techniques [17], by converting a set of 32 binary combinations of up and down positions of fingers into the equivalent decimal numbers of alphabets. A multi-color based encoding scheme [18] establishes the patterns of different ASL hand signs to provide an effective man-machine gesture based interaction. [19] proposed a static ASL hand gesture recognition system using edge oriented histogram and multiclass SVM for recognizing 24 American Sign Language alphabets. This system reported an overall accuracy of 93.75%. Hough Transform and neural networks were used to recognize ASL alphabets in [23]. This method achieved the overall recognition rate of 92.33%.

III. PROPOSED METHOD

The methodology of the proposed ASL finger spelling recognition system consists of the following stages.

a. Creation of Gesture dataset
b. Pre-processing
c. Canny Edge Detection
d. Feature Extraction
e. Gesture modelling and Classification

The generic flow diagram of the proposed ASL finger spelling recognition system is shown in Fig. 2.

A. Dataset

The benchmark Triesch ASL dataset [20] is used in this research work. This dataset contains 720 gray scale images, each having the size of 128 x 128 pixels with white, black and complex background. The dataset has 10 classes of ASL alphabets namely A,B,C,D,G,H,I,L,V and Y and each class of alphabet consists of 24 images. Only white and black background is considered in this work and complex background is not taken for study.

B. Pre-processing

Preprocessing is the set of operations done on an image before the feature extraction stage to enhance the quality of the image. This step involves image resizing, blurring, filtering of noise, contrast enhancement etc., As the benchmark dataset used in this work contains preprocessed gray scale images with suitable resolution and contrast, no preprocessing is required for further processing.

C. Canny Edge Detection

Canny edge detection is employed for finding the edges of input gray scale image. Since it detects as many real edges as possible, it is considered as an "optimal edge detector. In this work, we tried both Sobel and Canny edge detection methods. But Canny detects more edges when compared to Sobel edge detector. Usually, an edge detector would define the locations where the features exist in the image, whereas Hough Transform finds both the locations and the quantity of features existing in the image. Sobel edge detection method is not suitable because it hides many of the important details which represent the features as shown in Table I. However, Canny edge detector produces more unwanted edge details in the image. To solve this problem, different threshold values were used in trial and error fashion to remove the unwanted edges. Finally, a threshold of 0.4 was chosen since it gave a better recognition rate. Table II gives the canny edge detection results for sample gestures with and without a threshold of 0.4.

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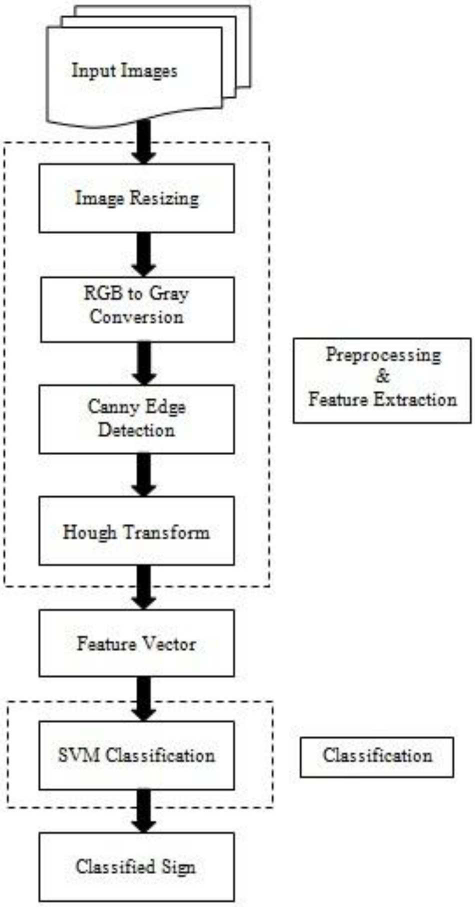
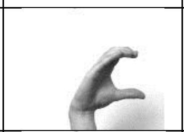
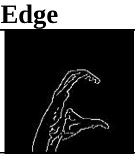
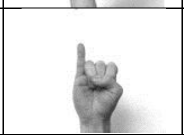
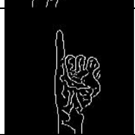
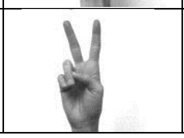
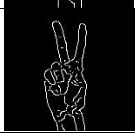


Fig. 2 Generic flow of the proposed system

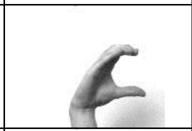
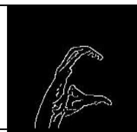
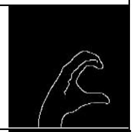
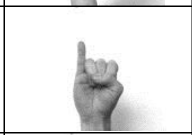
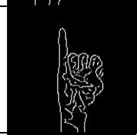
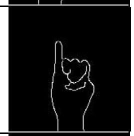
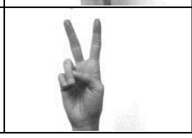
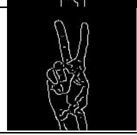
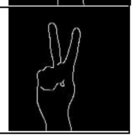
TABLE I
SELECTION OF SUITABLE EDGE DETECTION METHOD

Gesture	Input Image	Sobel Edge	Canny Edge
C			
I			
V			

D. Feature Extraction

After Canny edge detection, feature extraction is performed. In image processing, classical Hough Transform is used for feature extraction by identifying the lines in edge images. But the generalized Hough Transform identifies the position of arbitrary lines, circles and ellipses which are present in the edge images. As the extracted features have larger dimension, PCA is used for dimension reduction. The reduced features are stored as feature vectors, and they are applied as the input to the SVM for classification.

TABLE II
CANNY EDGE DETECTION WITHOUT AND WITH THRESHOLD

sadew	Input Image	Detected edges without threshold	Detected edges with a threshold
C			
I			
V			

E. Hough Transform

Hough Transform (Paul Hough,1962) is utilized to identify discretionary shapes, for example, lines, circles, ellipses and parameterized curves [21] from a binary image with intensity discontinuities. It transforms a Cartesian space into a parametric space (or Hough space). If two pixels (say P1, P2) lie on the same line in the Cartesian space, then for every pixel, all the conceivable lines passing through it can be represented by a solitary line in Hough space. Fig. 3. shows the mapping of P1 and P2 from Cartesian space into Hough space.

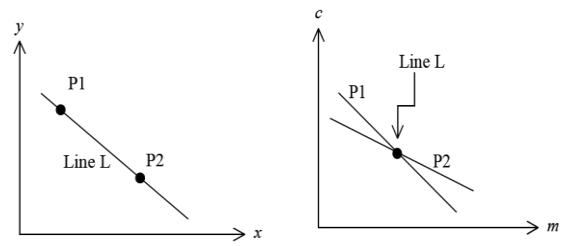


Fig. 3 Transformation of Cartesian space into Hough space

The line detection algorithm using Hough Transform is given below:

1. Find all the edges of the input binary image using a suitable edge detection technique.
2. Then, quantize the values of Hough space into a 2-dimensional matrix H.
3. Initialize the matrix H as zero.
4. Increment each element of $H(m_i, c_i)$ which corresponds to the edge pixel by 1.
5. Obtain the resultant histogram which shows the occurrence of edge pixels corresponding to the values of Hough Space (m,c).

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6. Consider only the large valued elements which represent the 'strong' lines in the binary image, by thresholding H.

When vertical lines exist in the image, infinite m values can occur. To avoid this problem, the alternative formulation was introduced by Duda et. al in 1972 by replacing the slope-intersect equation with normal equation and it is given as follows:

$$x\cos\theta + y\sin\theta = \rho \qquad (1)$$

Using the Eqn.(1), a point in Cartesian space can be represented as a curve in Hough space as shown in Fig. 4. Here 'ρ' is the length of the normal which is drawn from the origin to the line and 'θ' is the phase angle between the normal and the positive x-axis. The value of θ ranges from $-\pi/2$ to $\pi/2$. i.e., $\theta \in [0,180]$ and $\rho \in [-d, d]$ where d is the diagonal of the image.

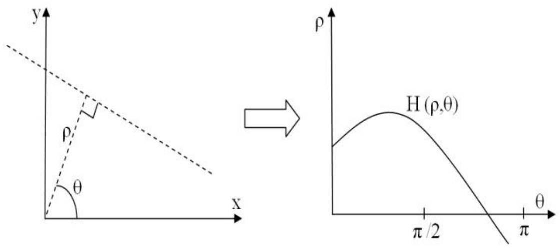

Fig. 4 Representation of a line in (ρ,θ) space

The representation of a line from image space to the Hough space is shown in Fig. 4. The main advantage of Hough Transform is that it detects the lines even from the noisy image.

F. PCA for dimensionality reduction

Curse of dimensionality is a major problem. Based on the values of ρ and θ, the dimension of Hough features varies. If the input feature vector size is larger, then the computational time would increase. Hence, the feature dimension must be reduced by projecting them into lower dimensional space. Principal Component Analysis is the most common technique for dimension reduction. In this paper, feature selection is not dealt with and only feature extraction is discussed. By using PCA, the dimension of the features is reduced and the feature vector is reshaped.

G. Gesture Classification by SVM

The basic principle of working of Support Vector Machine is Structural Risk Maximization (SRM). In general, SVM is suitable for pattern classification problems and non-linear regression. In SVM, a linear model is constructed to estimate the decision function using nonlinear class boundaries based on support vectors which are the points closest to the separating hyper plane. SVM trains the linear machines for an optimum hyper plane and the closest training points if the data is linearly separable. SVM maps the input vector into high dimensional feature space, if the linear boundary is inappropriate. By selecting the nonlinear mapping, the SVM constructs an optimal separating hyper plane in this high dimensional feature space. Table III shows the different types of SVM kernel functions.

TABLE III
SVM KERNEL FUNCTIONS

Type of Kernel	**Internal Product Kernel**
Polynomial	$(x^T x_i + 1)^P$
Gaussian	$\exp\left[\frac{\lVert x^r - x_i \rVert^2}{2\sigma^2}\right]$
Sigmoid	$\tanh(\beta_0 x^T x_i + \beta_1)$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed finger spelling recognition system was implemented in MATLAB R2013a. The training and testing of samples were run on a HP Laptop (2.4GHz Intel Core i3 Processor with 6GB RAM) running under Windows 7 operating system. Out of 480 grayscale images taken from the benchmark Triesch ASL dataset with uniform white and black background, 300 images were used for SVM training and 180 images were used for testing. During the training phase, the input feature vectors are used to train the SVM and a trained model is created for each class. Hence, 10 different models are created for all the 10 classes during the training stage. The size of each input feature vector which is fed to the SVM is 1x36 after dimensionality reduction by PCA. In the testing phase, a query image or test image is given to SVM. The class which the test image belongs to, is classified by the SVM based on the trained models. After classification, the meaning of the gesture is displayed in the form of text in a Graphical User Interface. Some of the sample gesture images used for testing are given in Fig. 5.

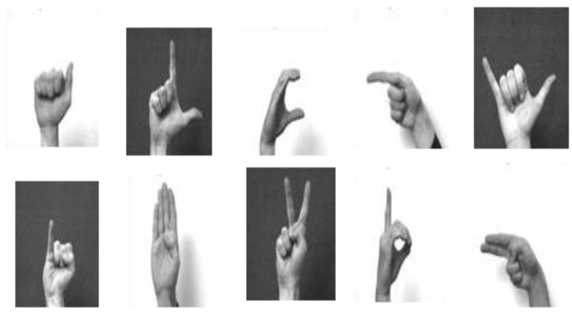

Fig. 5 Sample images used for testing

If the alphabet is finger spelled one after another continuously to form a word, it is displayed in the GUI so that the normal hearing people could understand the meaning of the gesture shown by deaf and dumb without any interpreter. The Hough space for the test samples which corresponds to the alphabets A and H are given in Fig. 6. The Hough space plotted in Matlab for the finger spelled alphabet A at θ =30° and ρ =1 is shown in Fig. 7.

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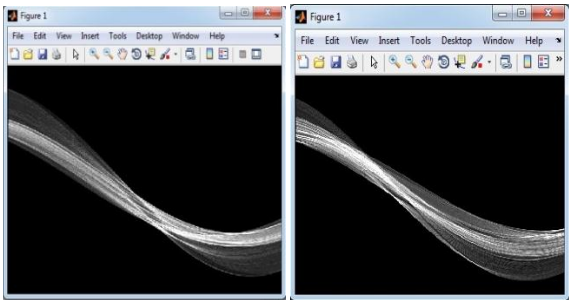

Fig. 6 Hough Space for the alphabets A and H

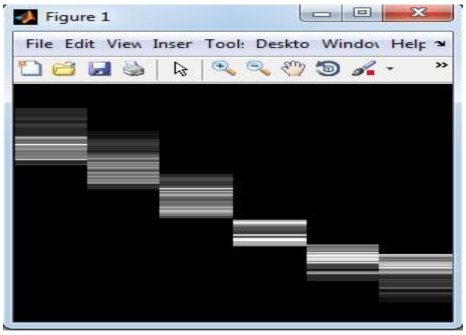

Fig. 7 Hough space for the alphabet A at θ =30°, ρ=1

Initially, we tested the benchmark dataset by taking 20 training samples per class without Canny threshold. The recognition rate achieved by the system during training and testing are given in Table IV.

TABLE IV
Recognition results without Canny threshold

Data	**No. of samples**	**Recognized samples**	**Recognition Rate (%)**
Training	200	200	100
Testing	180	108	60
Total	380	308	81

Since the achieved recognition rate is very poor, SVM is again trained with 25 samples per class for improving the classifier's performance and to get more satisfactory results. The testing results for improved training samples with a Canny threshold of 0.25 are shown in Table V.

TABLE V
Recognition results with Canny threshold (0.25)

Data	**No. of samples**	**Recognized samples**	**Recognition Rate (%)**
Training	250	248	99.2
Testing	180	152	84.4
Total	430	400	93.0

In an another experiment, we tried by training 30 samples per sign with canny threshold of 0.4 to improve the performance of the classifier further. We obtained the satisfactory results as shown in Table VI.

The recognition rate achieved for different SVM kernel functions is given in Table VII, when 300 training samples and 180 testing samples are used.

TABLE VI
Recognition results with Canny threshold (0.4)

Data	**No. of samples**	**Recognized samples**	**Recognition Rate (%)**
Training	300	299	99.6
Testing	180	169	93.8
Total	480	468	97.5

TABLE VII
Recognition rate for different SVM kernels

Type of Kernel	**Benchmark Triesch ASL Dataset**	
	Training	**Testing**
Gaussian	99.6	93.8
Polynomial	97	84
Sigmoid	98	78

V. PERFORMANCE MEASURES

The measures of the quality of recognition is derived from the confusion matrix [22] which gives the information about the actual and the predicted classification by the classifier. The performance of the classifier is measured based on the data available in the matrix. Table VIII shows the confusion matrix of SVM classification for Jochen Triesch dataset. In multiclass problem, the instances of more than two classes are classified using one against one (OAO) approach. The performance of the proposed ASL finger spelling recognition system is evaluated using the various metrics such as precision, recall, F-Score and accuracy. The performance measures of the system are tabulated in Table IX.

Accuracy:
Accuracy is the measure of overall effectiveness of the classier. It is defined as the ratio of number of instances correctly classified to the total number of instances made.

$$\text{Accuracy} = \frac{tp+tn}{tp+fn+fp+tn} *100 \qquad (2)$$

Where tp = true negatives, tn = true negatives, fn = false negatives and fp = false positives.

Recall/Sensitivity:
The percentage of positive labelled instances that are predicted as positive.

$$\text{Recall/Sensitivity} = \frac{tp}{tp+fn} \qquad (3)$$

Precision:
The percentage of positive predictions which are correct.

$$\text{Precision} = \frac{tp}{tp+fp} \qquad (4)$$

Specificity:
The percentage of negative labelled instances that were predicted as negative.

$$\text{Specificity} = \frac{tn}{tn+fp} \qquad (5)$$

F-Score:
F-Score is a measure of a test's accuracy.

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It considers both precision and recall of the test to compute the score. The best value of F-Score is 1 and the worst value is 0.

$$\text{F-Score}= 2 * \frac{\text{prescision}*\text{recall}}{\text{precision}+\text{recall}} \quad (6)$$

Recognition Rate:
The recognition rate or percentage recognition is defined as the ratio of the correctly recognized samples to the total number of test cases. i.e.,

$$\text{RR} = \frac{\text{number of correctly recognized samples}}{\text{Total number of samples}} * 100\%$$

TABLE VIII Confusion Matrix

Gesture	A	B	C	D	G	H	I	L	V	Y
A	16	1	0	0	0	0	1	0	0	0
B	1	15	0	1	0	0	0	0	0	1
C	0	0	18	0	0	0	0	0	0	0
D	0	1	0	15	0	0	1	0	1	0
G	0	0	1	0	17	0	0	0	0	0
H	0	0	0	0	1	17	0	0	0	0
I	0	0	0	0	0	0	18	0	0	0
L	0	0	0	0	0	0	0	18	0	0
V	0	0	0	0	0	0	0	0	18	0
Y	0	0	0	0	0	0	1	0	0	17

TABLE IX
Performance Measures of the proposed system

Gesture	Precision(%)	Recall(%)	F-Score(%)
A	94.11	88.88	91.42
B	88.23	83.33	85.71
C	94.73	100.0	97.29
D	93.75	83.33	88.23
G	94.44	94.44	94.44
H	100.0	94.44	97.14
I	85.71	100.0	92.30
L	100.0	100.0	100.0
V	94.73	100.0	97.29
Y	94.44	94.44	94.44

The system was initially trained with 200 samples without using any threshold for Canny edge. Since the performance of the system was very poor (60%) and the number of training samples without having reasonable orientation was small, the training data was increased further with canny edge threshold of 0.25. The results were much better than the previous. when 30 training samples per sign is used with canny threshold of 0.4, satisfactory recognition results were obtained. Hence the training of the system was stopped as there was no significant improvement of recognition beyond this threshold value. Table X shows the overall recognition accuracy achieved by the system.

TABLE X Overall Recognition Accuracy

Sign	Recognized Samples	Misclassified Samples	Recognition accuracy (%)
A	16	2	88.88
B	15	3	83.33
C	18	0	100.0
D	15	3	83.33
G	17	1	94.44
H	17	1	94.44
I	18	0	100.0
L	18	0	100.0
V	18	0	100.0
Y	17	1	94.44
Total	169	11	**93.88**

The simulation results prove the efficiency of the proposed system by recognizing the finger spelled ASL alphabets from the bare hand images without using any sophisticated hardware or data gloves. It achieves the overall accuracy of 93.88% and it is shown that our approach is superior than the existing approaches. Table XI shows the comparison of various methods in the recognition of ASL gestures.

TABLE XI
Comparison of proposed method with existing techniques

Sl. No	Name of the technique	Classifier used	Recognition accuracy (%)
1.	HOG	BPNN	91.6
2.	EOH	SVM	93.75
3.	SIFT	Point Pattern Matching	77.77
4.	Geometric Features based	BPNN	80.28
5.	Color Based	Template Matching	93
6.	Proposed Method (Hough Transform + SVM)	SVM	93.88

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For simplicity and convenience of the user, a graphical user interface (GUI) is created in MATLAB so as to display the meaning of the static hand gesture in the text box provided in it. This GUI is much helpful for the deaf and dumb community to communicate with the normal hearing persons without any interpreter.

The vision based image processing technique automatically interprets the finger spelled ASL alphabets in the text format using the bare hand, thereby eliminating the sophisticated hardware or sensors. The time taken to train all the input samples is 240 seconds and the average recognition time during the testing phase is calculated as 0.8 seconds.

The GUI of the proposed ASL finger spelling recognition system is given in Fig. 8.

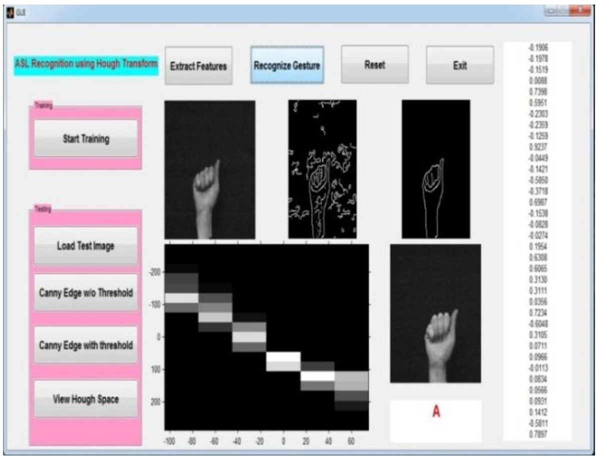

Fig. 8 GUI of the proposed system

VI. CONCLUSION AND SCOPE FOR THE FUTURE WORK

This work focuses on vision based recognition of finger spelled American Sign Language alphabets in an automated manner. The proposed work is based on Hough Transform features and it is more efficient and reliable since it is able to recognize the hand gestures from static images using simple image processing technique.

The main advantages of this system are its speed, robustness against rotation and scaling and it does not require the user to wear data gloves or sensors for recognition purpose. In future, the system can be extended for recognizing the hand gestures from complex background in real time.

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