Classifying Hand Gestures using Back Propagation Neural Network

Fatima Sufi
Department of Information Technology
Chandigarh Engineering College, Landran, Mohali, Punjab, India

Jaskiran kaur
Department of Computer Science and Engineering
Chandigarh Engineering College,Landran,Mohali,Punjab,India

Abstract - Hand gesture recognition is attaining adoration among varied human-machine communications, allowing humans to connect and co-operate with computers naturally. The prime aim of hand gesture identification is to develop a system that is made to understand hand actions and in return conveys valuable information peculiarly to the deaf and dumb people. However, the major problem encountered in hand a gesture interpreting system which still remains unsolved is to handle the data at the time of training and testing hampering with the performance of the system.Therefore, the main objective of this paper is to make the classification error minimal by using Back Propagation Neural Network as a hand gesture identifier so as to improve performance in terms of accuracy, false acceptance rate, false rejection rate, mean square error and precision.

Keywords - Gesture recognition, BPNN, Accuracy, FAR, FRR, MSE, precision.

I. INTRODUCTION

Hand gesture recognition is commonly used in human-computer interface to build user interfaces which are elementary and simple to use and learn [1-3].Gestures may be static or dynamic. In former, the posture of hand indicates the emotion or feeling and in latter a sequence of hand poses is used to determine the movement of hand. We have carried our work on dynamic hand gestures. For every hand gesture recognition system, it is mandatory that the hand is segmented properly because unclean data will yield inaccurate or low quality image data results. The input image is always a colored image and needs to be converted to grayscale or edge form in order to reduce the number of pixels in an image so that segmentation on hand becomes easy. Segmentation checks for noise attacks on image because degraded image will not be segmented. The limitation of hand gesture recognition system lies in its improper classification which was earlier done with Artificial Neural Network though is considered one of the best classifiers. The classification is done to test the system under various conditions. In this paper, we have used Back Propagation Neural Network for classifying the gestures and to identify them with greater precision and accuracy. In comparison to Artificial Neural Networks, Back propagation neural network sends the optimized data in multiple layers rather than in a single layer. Artificial neural network is a mathematical model for information clarifying process and is symmetrical to the biological neural network. Throughout the feature detection stage, the ANN classifier is trained to identify the user's hand gesture. In the testing phase, the features are extracted in the same way as in training phase [4].

II. METHODOLOGY

A. Feature Extraction using Scale Invariant Feature Transform Algorithm

SIFT is an algorithm to find and track local features of an image to perform reliable identification. The features which are extracted from SIFT are detectable even under the varying illumination and noise conditions [5-6]. SIFT works as follows:

1. Evaluate the Gaussian scale-space

input: u image

output :v scale-space

2.Calculate the Gaussian difference (DoG)

input: v scale-space

output: w DoG

3. locate candidate key features (3d discrete extrema of DoG)

input: w DoG

output: {(xd, yd, σd)} a discrete extrema (location and size)

4. Improve candidate keyfeature location with sub-pixel accuracy

input: w DoG and {(xd, yd, σd)}

output: {(x, y, σ)}

5. clean bad key points because of noise

input: w DoG and {(x, y, σ)}

output: {(x, y, σ)} list of distilled key features

6.clean imbalanced key points located on edges

input: w DoG and {(x, y, σ)}

output: {(x, y, σ)}

7. Allot a reference orientation to every key feature

input: (∂mv, ∂nv) scale-space gradient and {(x, y, σ)} list of key features

output: {(x, y, σ, θ)} oriented keypoints

8. Develop the key feature descriptors

input: (∂mv, ∂nv) scale-space gradient and {(x, y, σ, θ)} described keypoints

output: {(x, y, σ, θ,f)} list of elaborated key features

B. Genetic algorithm

Vital solutions to optimization problems using operators like selection, mutation and crossover[7-8] are carried out by using genetic algorithm. It requires a fitness function to generate best solutions. It accomplishes its task as under

```
// Begin with an initial time
        t := 0;

// initialize a usually  general population of individuals
        Init population P (t);

// check fitness of all primary individuals of populace
        evaluate P (t);

// check for the completion condition(time, fitness, etc.)
        while not terminating do

// increment the time counter
      t := t + 1;

// choose a sub-population for generating offspring
        P' := selectparents P (t);

// rejoin the "genes" of selected parents
        recombine P' (t);
```

```
//  disturb and unsettle the mated population
                 mutate P' (t);

//  compute its next fitness
                 evaluate P' (t);

// choose the survivors from original fitness
                 P := survive P,P' (t);
               od
    end GA.
```

III. BACK PROPAGATION NEURAL NETWORK

A. Overview of BPNN

In 1969, an algorithm for learning in multi-layer network, Back propagation (or generalized delta rule), was built by Bryson and Ho. This algorithm is best to identify the distance of a training algorithm. The training data is used to adjust weights and edges of neurons. This is done to minimize the network classification errors of scheming. It is slow –going and undemanding than gradient descent and is an easiest algorithm to learn.Back propagation implements by using the gradient descent method to a feed forward system.

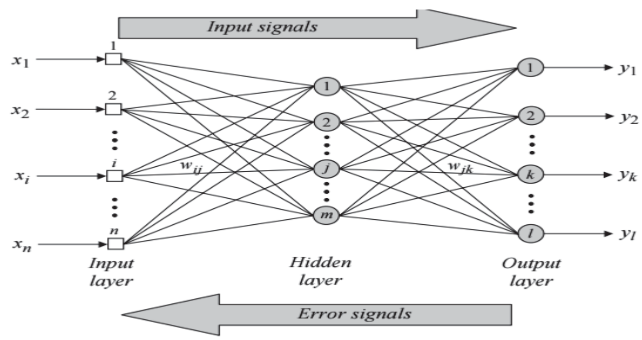


Fig1: Back Propagation Neural Network

B. Feed forward training of input patterns

– Every input node gets a signal, that is broadcast to other hidden units

– Each hidden unit evaluates its activation function which is broadcasted to other output node

C. Back propagating of errors

– Each output node connects its activation with the required output

– Based on these changes, the error is propagated back to previous nodes

D. Adjustment of weights

– Weights of all joins evaluated simultaneously depending on the faults which were traced back.

This algorithm uses guided learning, for the network to compute, and then the error difference of actual and predicted results is calculated. Back propagation algorithm helps to decrease this error, until the ANN understands the training data. The training starts with random weights, and the focus is to fix them so that the error will be terminated [9-11]. If a neural network consists of P processing units, then input/output function is described as :

k = L(mW)

where m = ***{m,)*** is the input vector to the system,

k = {Kkj }is the output vector from the system,

W is the weight matrix. It is later defined as

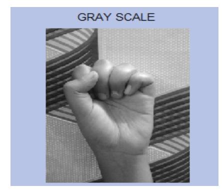
$W = (w_i^T, wj^T, ..., Wn^T)^T$

Where in vectors w_i,wj,...,Wn are the individual PE weight vectors, given as

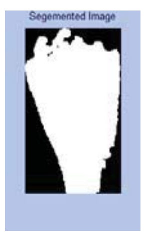
$$W_t = \begin{matrix} w_i \\ wj \\ wn \end{matrix}$$

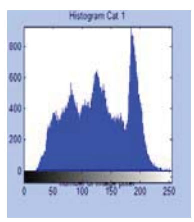
IV. RESULT ANALYSIS

In our proposed work we have chosen a numeric dataset with six different categories of images.Our focus is on dynamic hand gestures recognition.The procedure goes as follows; the input image is uploaded from one of the categories of images in the dataset.This image undergoes segmentation,this image is transformed to grey scale and edge form.Segmentation of the image is a must to get a noiseless and clean image. Once the segmentation is done, the resultant image appears in the form of histogram.The next step after segmentation is extracting the key features from the segmented image data. We have done feature extraction using SIFT algorithm. Once the feature extraction has been done, there arises a need for an optimal result to make the recognition secure.The optimization is carried using genetic algorithm and optimal solution appears in the form of optimized graph as shown in below figures.

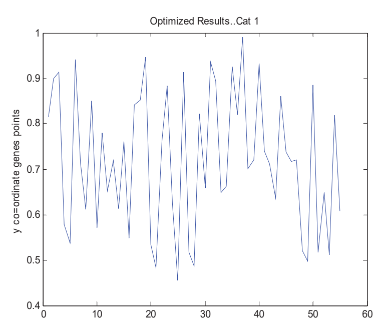


(a) uploaded image for recognition (b) grey scale of image for pixel reduction





(c) segmented image (d) histogram of image in graphical form



(e) key point localization (f) reduced image

Fig2: various steps for gesture recognition shown in above figures

Categories	Mean square error using ANN	Accuracy using ANN
Cat1	0.065435	74.228
Cat2	0.064815	17.1802
Cat3	0.065636	75.3243

Cat4	0.065828	5.4716
Cat5	0.068359	64.4872

Table 1: Results calculated using previous method

Categories	Mean square error using BPNN	Accuracy using BPNN
Cat1	**0.10791**	**99.9294**
Cat2	**0.10791**	**99.4497**
Cat3	**0.10791**	**99.4569**
Cat4	**0.10791**	**99.882**
Cat5	**0.10791**	**99.1457**
Cat6	**0.10791**	**99.3124**

Table 2: Results calculated using proposed method

Categories	FAR	FRR	PRECISION
Cat1	0.00052696	0.00017897	99.9473
Cat2	0.0053323	0.00017097	99.4668
Cat3	0.0052603	0.00017109	99.474
Cat4	0.0010021	0.00017818	99.8998
Cat5	0.0083768	0.00016589	99.1623
Cat6	0.0067077	0.00016867	99.3292

Table 3: Results calculated by above parameters using BPNN

The optimized results are followed by classification using BPNN which returns the best possible output in terms of accuracy and minimal classification errors.

The results calculated are based on the following parameters.

1. Accuracy

Accuracy defines the closeness a measured value to the true value. In this proposed work our system has achieved 99% accuracy by using BPNN as a gesture classifier. In comparison to the previous approach(ANN) that achieved 95% accuracy. The graph of both the accuracy methods shows that our system is more accurate. The accuracy values obtained from graphs are shown in table 1 and table 2 respectively.

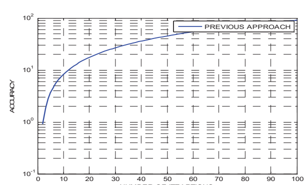


Fig3: accuracy (previous)

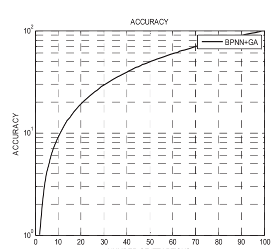


Fig4: accuracy(proposed)

2. FAR(False Acceptance Rate)

A system's FAR is termed as the ratio of the number of false acceptances and the number of recognition trials. The values achieved for number of iterations using proposed method are represented in table3

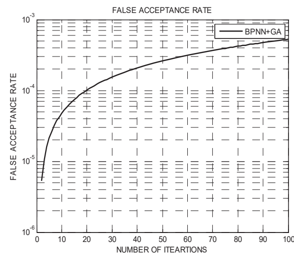


Fig5: FAR(proposed)

3.FRR(False Rejection Rate)

A system's FRR can b termed as the ratio of the number of false rejections over the number of identification trials. The FRR graph is shown below and the values obtained for a category for various iterations is depicted in table 3.

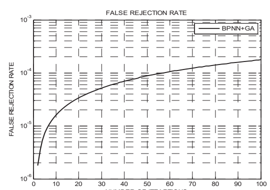


Fig6:FRR (Proposed)

4. Precision

Precision is stated as the ratio of the number of resembling records over the total number of non-resembling and resembling records attained.Our proposed system obtained a precision of near about 99%.

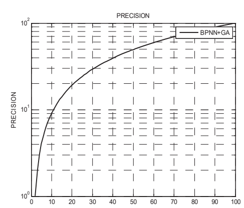
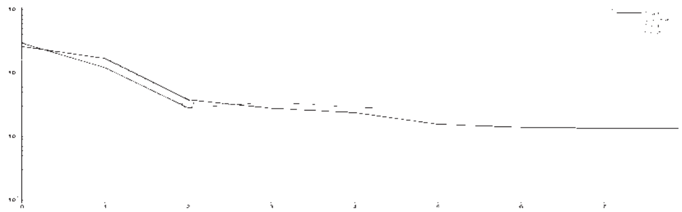


Fig7: precision(proposed)

IV. EXPERIMENTS AND DISCUSSION

The following figures shows the performance of the trained Back Propagation Neural Network, determined by validation performance between the number of iterations and the mean squared error. The best validation performance estimated is 320.7129 at epoch of 2 shown in fig8. This result can be accepted due to the small mean square error. However, the regression analysis illustrates that, the correlation coefficient equals to 0.72506 which can be seen from fig 9, between the output and the target for training; which means that the both output and target are very close, which represents excellent fit. We carried out experiments with different users hand images to evaluate the performance of the ongoing hand gesture classifying method represented in fig10. Each user takes three seconds to carry out his gestures. This hand gesture classification was performed on Windows 7 with MATLAB R2010a.The performance of the proposed algorithm was evaluated based on the accuracy, which calculates the ability to correctly classified user's hand gestures to their corresponding input user's hand gestures with faster response time.

Best validation performance is 320.7129 at epoch2



8 Epochs

Fig8: BPNN training performance

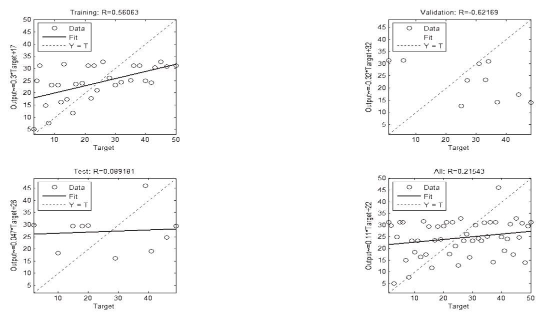


Fig9: Regression analysis using BPNN

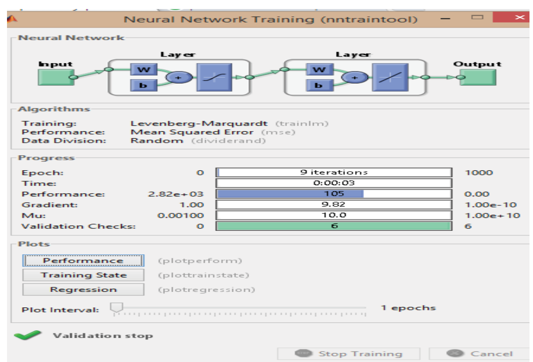


Fig10: Above figure describe the performance of the recognition system , training module generate, classification. BPNN uses the inbuilt function like Levenberg-Marquardt to calculate the mean of the error.

V. CONCLUSION AND FUTURE SCOPE

The hand gesture recognition system that is considered is tested with different gestures and is able to categorize it correctly. A new technique is planned to increase the accuracy of gesture recognition system using Back propagation Neural Network, GA and SIFT. We have compared proposed method with previous implemented method. From the results, it has been clearly seen that results for proposed method are good in comparison to earlier method. In addition, the search procedure can be enhanced to increase the presentation of the system. The proposed system is capable of classifying only the static images that can be enhanced further to recognize hand gestures in video as well. The results can be improved using Genetic Algorithm instead of Back propagation neural network and Support Vector Machine. In future instead of offline recognition system an online recognition system can be designed.

REFERENCES

[1] Reddy, K. Sivarajesh, P. SwarnaLatha, and M. RajasekharaBabu. "Hand Gesture Recognition Using Skeleton of Hand and Distance Based Metric."Advances in Computing and Information Technology. Springer Berlin Heidelberg, 2011. 346-354.
[2] Suarez, Jesus, and Robin R. Murphy. "Hand gesture recognition with depth images: A review." RO-MAN, 2012 IEEE. IEEE, 2012.
[3] Kim-Tien, Nguyen, Nguyen Truong-Thinh, and Trinh DucCuong. "A Method for Controlling Wheelchair Using Hand Gesture Recognition." Robot Intelligence Technology and Applications 2012. Springer Berlin Heidelberg, 2013. 961-970.

[4] Jalab, Hamid A., and Herman Omer. "Human computer interface using hand gesture recognition based on neural network." Information Technology: Towards New Smart World (NSITNSW), 2015 5th National Symposium on. IEEE, 2015.

[5] Zhou, Yimin, et al. "Hand Gesture Recognition Based on the Parallel Edge Finger Feature and Angular Projection." Computer Vision-ACCV 2014Workshops. Springer International Publishing, 2014.

[6] Li, Zisheng, et al. "Evaluation of medical image registration by using 3D SIFT and phase-only correlation." Abdominal Imaging. Computational and Clinical Applications. Springer Berlin Heidelberg, 2012. 255-264.

[7] Wu, Chih-Hung, Wei-Lun Chen, and Chang Hong Lin. "Depth-based hand gesture recognition." Multimedia Tools and Applications (2015): 1-22.

[8] Justina, J. P., and SangeethaSenthilkumar. "A Survey Analysis on: Vision-Based Hand Gesture Recognition." International Journal 4.1 (2014)

[9] H, AL-JBARA.M, KIAH. H.A, JALAB.2012. Increased capacity ofimage based steganography using artificial neural network. AIP Conf.Proc, 2012. 20-25.

[10] Jagdish Lal Raheja, Umesh Kumar, Human Facial Expression Detection Image Using Back Propagation Neural Network., International Journal of Computer Science and Information Technology (IJCSIT); Vol. 2, No. 1,Feb 2010, pp. 116-112

[11] A.Bosch, A. Zisserman, and X. Munoz, Scene classification using hybrid generative /discriminative approach, IEEE Transactions on Analysis and Machine Intelligence, vol. 30, no. 4, pp. 712-727, 2008,993-1007.