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Static Hand Gesture Recognition Using SOM-Hebb Classifier

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Abstract: Gestures are physical actions made by human to convey feelings or expressions to others. Hand gestures are basically classified as static and dynamic. It is used as sign language for deaf and dumb, controller less video gaming, Smart TV, video surveillance, human robot interaction, biometrics, virtual and augmented real time applications. This proposed work focuses on static hand gesture recognition system using hybrid network consisting of SOM (Self-organizing map) and Hebb classifier. SOM classifier is a single layer feedforward neural network. It uses Hebbian learning algorithm to in its association to help in identifying categories. Mapping is done by SOM method and network training is obtained by Hebbian learning algorithm. The performance of this proposed work is simulated using MATLAB and evaluated in terms of recognition accuracy. The obtained accuracy of the system is 91.11%.

Keywords: Euclidean distance, Fourier descriptor, Hebb, Self-organizing maps (SOM), Skin color Segmentation.

I. INTRODUCTION

Gestures are kind of action or movement performed by human beings for conveying message. Hand gestures are the main way of communication for deaf and dumb people. Because of lack of understanding interpreters are used. In today's advanced world this problem is nearly removed and many applications are there for deaf and dumb people. Hand gestures are mostly used in real time application namely 3-D gaming, robot control and video surveillance. Hand gestures are many two types static based (posture based i.e. without any movement) and dynamic based which include movement of hand for a particular period of time. One can used single handed signs or both handed sign [1].Hand gestures contain a different approach that is various types of input taking styles which are basically gloved based and vision based [2]. Glove based include data glove (hardware based, sensors embedded on the glove) and colored glove it includes the different color patches used on a single glove or either single and two or more colors [3]. Another includes the vision based it consists of the input taken of bare hands. It needs a good quality camera (Kinect etc).It is further divided into appearance based and 3D based approach [2][3]. The proposed work is based on static hand gesture using SOM- Hebb neural classifier [1]. The whole process consists of image acquisition (capture RGB image), pre-processing of image (skin color segmentation and vertical and horizontal projections), feature extraction (calculating magnitude spectra using FDT (Fourier Descriptor Transform)), classification (by using SOM-Hebb classifier) for feature vector and accordingly recognize the desired hand sign.

This paper is organized as follows: the Section II demonstrates the work related to hand gesture recognition. In the Section III the methodology is studied. Section IV is about the experimental results and the section V is followed by conclusion.

II. RELATED WORK

Hand gesture recognition technology is very well known research topic in image, video processing and real time applications. Much research work has been carried on it.

A novel FPGA implementation of hand sign recognition system with SOM–Hebb classifier proposed by Hiroomi Hikawa and Keishi Kaida [1] shows the hand sign recognition of American Sign Language (ASL) using SOM –Hebb hybrid classifier. The recognition system based on the video processing and is implemented by using FPGA. Adithya V., Vinod P. R., Usha Gopalakrishnan [4] presented a method on Artificial Neural Network (ANN) based method for ISL Recognition. This method uses the Fourier Descriptor for feature extraction, statistical features in terms of central moments (variance, skewness and kurtosis) and classification by using ANN. In [5] Sweta Shiwani, Neeraj Shukla, Abhishek Kumar showed comparison between unsupervised feature learning method like Softmax classifier(Auto- Encoder) with the SOM (Self-Organizing Map Algorithm) classifier algorithm. The SOM shows better result as compared with Softmax algorithm. In [6] Hsien-I Liny, Ming-Hsiang Hsu, Wei-Kai Chen proposed a method on human hand gesture recognition using a convolution neural network. the vision based gesture recognition is done using CNN (Convolution Neural Network).By using CNN the images are easier to recognize, while due to light intensity problem gesture seriously affect recognition. In [7] Yuan Yao and Yun Fu presented the gesture recognition is done on the basis of contour model using Kinect sensor (RGB –D sensor). It is able overcome the problem of illumination. It cannot handle the segmentation of long arm or body and has limited accuracy. Deepika Tewari, Sanjay Kumar Srivastava [8] proposed the visual static hand gestures recognition using KSOFM (Kohonen Self Organizing Maps) using ISL(Indian Sign Language) along with

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discrete cosine transform (DCT) for feature extraction. In [9] Hiroomi Hikawa, Seito Yamazaki, Tatsuya Ando, Seiji Miyoshi, Yutaka Maeda compared Range Check (RC) classifier and hybrid network of SOM –Hebb network. The efficiency of hybrid network is much better than RC classifier. [10] The similar classifier i.e. hybrid network (SOM - Hebb) is used for recognizing Japanese sign language of 41 signs. It contains 22 dimensional vectors including 100 neurons to have high recognition performance.

III.HAND GESTURE ALGORITHM

The main purpose of this system is to recognize the gesture/sign and enhance recognition accuracy. The hand sign used in this work is ASL (American Sign Language) which has been taken from the Massey University. The flow of methodology consists of following processes:

A. Pre-processing.
B. Feature Extraction.
C. Classification.

The hand gesture system block diagram is shown in the Figure 1. A colored image i.e. RGB format image is taken from a camera or reference dataset of hand sign. The image contains equal pixels i.e. S x S values i.e. of equal height and width. The input image is converted to binary image using Skin color segmentation by YCbCr color space. The pre-processing is further done on binary image of I(x, y) which contains binary pixel values .The brightest pixel values are count in two ways horizontally and vertically to get a vector of size of image height and width in form of projection. These projection values are differentiated based on height (horizontal projection) i.e. $H_P(y)$ and based on width (vertical projection) i.e. $V_P(x)$. The final stage of pre-processing is using two Fourier transform coefficients i.e. Fourier Descriptor for computing or calculating the magnitude spectrum H (n) and V (n) of $H_P(y)$ and $V_P(x)$. Both of these are used as feature vector of the input image.

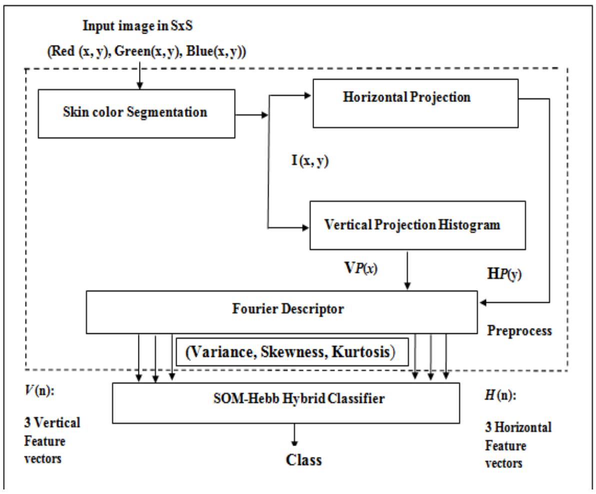

Fig 1 The block diagram of hand gesture recognition system

The feature of (D = 6) dimension (i.e. 3 feature vectors in terms of higher order moments i.e. variance, skewness, kurtosis) is fed to the SOM – Hebb classifier network that classifies the G class of gesture and identifies the hand sign.

A. Pre-Processing

The preprocessing is prior stage of gesture recognition system. It includes image capture (Image aquistion), then converting into gray scale or binary image In this paper skin color segmentation, horizontal and vertical projection is used for reducing the dimesions. These values are used to convert into magnitude spectra using fourier descriptor. The Figure 2 describes the numerical dataset of ASL (American sign language) consisting of 0 to 9 numbers.

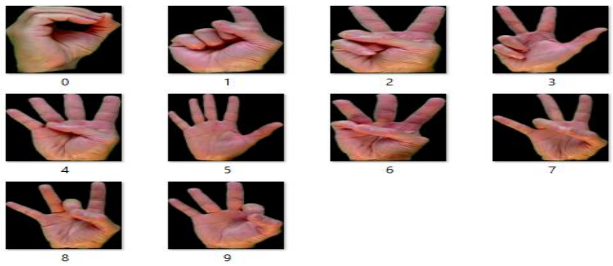

Fig 2. The Massey University hand sign dataset consisting of numbers 0 to 9 [11].

• Skin color segmentation:

In the process of skin color segmentation in the input image it is first converted to YCbCr color space. YCbCr separates RGB into luminance and chrominance components where Y is the luminance component and Cb, Cr are the chrominance components [4]. RGB values are converted into YCbCr color space using the weighted sum of RGB. Using thresholding condition the output of hand segmentation is obtained. If the Y, Cb and Cr values of a pixel are within a specific range of skin color, the pixel value is set such that pixel would be white otherwise black. Thus a pixel is described as belonging to skin if it satisfies the following relation:

$$75 < Cb < 135 \text{ and } 130 < Cr < 180 \text{ and } Y > 10. \quad (1)$$

The output of this color segmentation is binary image in terms white for skin color and black for black background of color image [4]. The resultant binary image may contain noise, that why median filtering is used to remove the noise.

• Horizontal and vertical projections:

The horizontal and vertical projection histograms of I (x, y), are calculated in the preprocessing as a sub module. The projection is defined as an operation that maps a binary image into a 1-D array called a histogram. The histogram value is the sum of pixel values along a particular direction (horizontal and vertical) according to is width and height. Horizontal projection histogram H_P (y) and vertical projection histogram V_P (x) are defined by:

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$$H_P(y) = \sum_{x=0}^{S-1} I(x,y) \quad (2)$$
$$V_H(x) = \sum_{y=0}^{S-1} I(x,y) \quad (3)$$

B. Feature Extraction

The main purpose of the feature extraction is to reduce the original dataset by measuring features in terms of shape that differentiates on input pattern. The features extracted are transformed in feature vectors. Fourier coefficient i.e Fourier shape descriptor is used as shape transform. Also the statistically normalized feature vectors are used in terms of central moment.

• Fourier Descriptor

The Fourier transform is used to convert the H_P (y) and V_P (x) projections into the magnitude spectral value i.e. H (y) and V(x). Fourier Descriptor (FD) is obtained by applying Fourier transforms to a magnitude spectrum. The feature extracted (in terms of shape) is a 1D function in general. Normalized Fourier transformed coefficients are called Fourier Descriptor for the shape. Fourier descriptors of the row (horizontal) and column (Vertical) projection vectors are calculated. These descriptors represent the handshape in the frequency domain. Fourier descriptors have strong discrimination power, they remove the noise sensitivity present in the shape representation of image [4].Fourier descriptors are information preserving and they can be easily normalized. For the two vectors X (t) and Y (t), where t=0, 1, 2... S-1 the discrete Fourier transforms are used is given by,

$$Hn = \frac{1}{S}\sum_{t=0}^{S-1} X(t) \, . \, e^{-\frac{j2\pi nt}{S}} \quad (4)$$

$$Vn = \frac{1}{S}\sum_{t=0}^{S-1} Y(t) \, . \, e^{-\frac{j2\pi nt}{S}} \quad (5)$$

where n= 0,1,2….. S-1 for both X and Y. S is the size of X and Y. Hn and Vn are the vertical or horizontal Fourier descriptors of the shape. The feature values are formed from the Fourier descriptors of the horizontal and vertical projection vectors by taking only the magnitude of the Fourier coefficients and ignoring the phase information. Normalization of feature vector is carried out to remove the unwanted information and store the main information. The feature values are normalized by dividing the magnitude values of all the Fourier coefficients by the magnitude value of the first coefficient which is called the dc component.

$$Hnm=Hn/Hn(1) \quad (6)$$

$$Vnm=Vn/Vn(1) \quad (7)$$

where, Hnm and Vnm are the magnitude values or spectra of the horizontal and vertical projections.

• Statistical Feature Vectors(Central Moments)

The feature vector is formed of six feature values which are the second, third and fourth central moments of the normalized Fourier coefficients of the horizontal and vertical projection vectors for each gestures. Central moments are a set of values which contains the probability distribution properties. The higher order central moments are only related to the spread and shape of the probability distribution, other than location. So they are preferred to ordinary moments for describing the probability distribution.

The six statistical features namely variance, skewness, kurtosis of both horizontal and vertical projections are extracted.

A. Variance

Variance is a measure of the scattered data in a sample. It is also a good descriptor of the probability distribution of a random variable. It describes the spread of the numbers from the mean value. The μ_2 represents the second order moment. In equation (9) shown below μ is the mean, X_i is the sample value of random variable where, i= 1,2….,N. N is the finite set of data values of the random variables.

$$\mu_2 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2 \quad (8)$$

B. Skewness

The histogram can be divided at the center into two identical halves, wherein each half is not a mirror image of the other, is called as skewness. Skewness is the measure of a single value which indicates the degree and direction of asymmetry. The μ_3 represents the third order moment.

$$\mu_3 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^3 \quad (9)$$

C. Kurtosis

Kurtosis is a parameter that describes the shape and is a measure of the "peakedness" of a random variable's probability distribution. It contains the characteristics of the distribution of a real-valued random variable same as that of skewness. The μ_4 represents the fourth order moment.

$$\mu_4 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^4 \quad (10)$$

C. Classification.

It is the last phase of the gesture recignition system.After this step the input gesture is recognized in terms of the numerals. The classifier used in this paper is combination of SOM- Hebb Classifier. Along with SOM-Hebb classifier, the Euclidean distance for increasing accuracy.

• SOM – Hebb Classifier

The statistical DFT based normalized six feature vectors are given as input to the SOM-Hebb (Hybrid Network).Each vector of the element ξ_i is fed to the classifier network. SOM is an unsupervised single feedforward neural network which is trained Hebbian learning algorithm. A winner neuron is determined from the vectors of neuron and its neighbourhood neurons are updated. The Hebb network identifies the category from winner neuron in terms of class. Classifier takes the D - dimensional vectors from pre-processing and classifies them into H classes (where 'H' is hand sign class, here D= 6 feature vectors). Fig. 3 shows the schematic block diagram of the SOM-Hebb Classifier.

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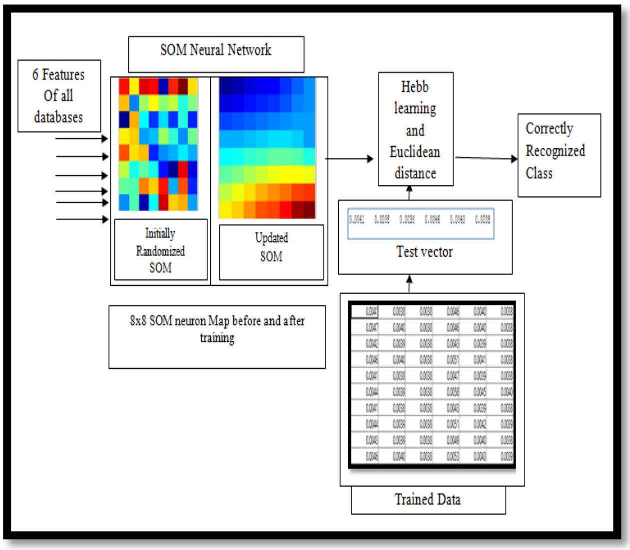

Fig. 3. SOM-Hebb Classifier

SOM - Hebb neural network algorithm:

Step 1: Take the statistical feature vector as input to the SOM neural network.

Step 2: SOM consist of learning (SOM map trained with training vectors) and recall phase (mapping or testing done by using trained map).

Step 3: The input weight vector are initially randomly generated (training data) each of which contains a D-dimensional vector $\vec{w_i}$ called the weight vector

$$\vec{w_i} = \{wi0, wi1, \ldots, wiD{-}1\} \in \Re^D. \quad (11)$$

Step 4: In learning process the input vectors, x ∈ D, are given to the map in multiple iterations (epoch). For each input vector, the distances to all weight vectors are calculated.

$$x = \{x0, x1 \ldots xD{-}1\} \in D. \quad (12)$$

Step 5: Learning rate of epoch (initial and current) is computed. The variance of the gaussian (Neighbourhood) function is computed for current epoch.

Step 6: The neuron having the weight vector closest to the input vector is searched and is called a winning neuron. The weight vectors of the winning neuron and its neighbourhood neurons are updated to be closer to the input vector.

$$w_i(t+1) = w_i(t) + hc_i \cdot d_i \quad (13)$$

where, t is a sampling index.

Step 7: Compute the Euclidean distance between the training vector and each neuron in the SOM map. Find the best match unit (BMU) and transform it into 2D map to find row and column of winner. The winner neuron is calculated using Euclidean or Manhattan distances. The winner neuron is given by,

$$H = \arg \min_i \{\|\vec{x} - \vec{wi}\|\} \quad (14)$$

The Manhattan distance d_i is given by

$$d_i = \sum_{j=0}^{D-1} |x j - wi j| \quad (15)$$

Step 8: Find the association matrix and generate a gaussian function centered on the location of the BMU. Determine neighbouring neurons and determine the size of it.

$$h_{ci} = \alpha(t) \exp\left(-\frac{\|\vec{r_c} - \vec{r_i}\|}{2\sigma^2(t)}\right) \quad (16)$$

where , $r_c \in \Re^2$ and $r_i \in \Re^2$ correspond to the location vectors of the winner neuron-c and neuron-i .

Step 9: For SOM weights updation, the BMU neurons are put back to the SOM map.

Step 10: The SOM map obtained is used for mapping from neurons to cluster in winner find module. The mapping is done by hebb i.e association map. It again determines the count of how many times the neurons are interconnected to the cluster.

Step 11: The SOM map and the trained feature data (teaching) are used for comparison and once again Euclidean distance is calculated to find the winner class by computing the activation map (trained SOM map) and the testing vector.

Step 12: The Hebb synchronizes better with strong simultaneous correlation between cluster and teaching data.

Step 13: On giving testing vector as input the same class vector is expected.

Step 14: The training and testing is done. If not then go to step 3-13.

- Euclidean and Hamming Distance

The Euclidean distance along with hamming distance is used as a classifier along with SOM- Hebb to increase the recognition accuracy. The Euclidean distance is nothing but the square of difference between two points or two vectors i.e. training and testing vectors.

$$E(i, j) = |(\mathbf{x1} - \mathbf{x2}) + (\mathbf{y1} - \mathbf{y2})| \quad (17)$$

E (i,j) is the Euclidean distance vector, where x, y are the two co-ordinates of the vectors i,j, where i,j= 1,2.
The distance vector is calculated in terms of multiplication of multiplier count and the E (i,j).The minimum distance of the Euclidean distance vector is considered as correct class or hand sign position vector.

IV.EXPERIMENTAL RESULTS

The implementation results of the proposed hand sign recognition system is presented in this section. The system was implemented using MATLABR2010a in a machine with Intel(R) Core(TM) i5, 2.40 GHz processor, 64 bit OS system type and 4GB RAM. The 5 signer database is used by the Massey university signers. Total 9 databases of numerals 0 to 9 are taken for training and testing purpose. The results obtained are pre-processing, statistical feature graph, SOM training map, confusion matrix and finally GUI (Graphical User Interface).The pre-processing result of the hand sign '0' showing six images of the colored image, skin color segmented image, the horizontal and vertical projection along with it the magnitude feature vector plot of horizontal and vertical projection as shown in the fig.4. The last two image of

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magnitude spectra are position invariant for the input image and remain same for the one signer but different for other signer.

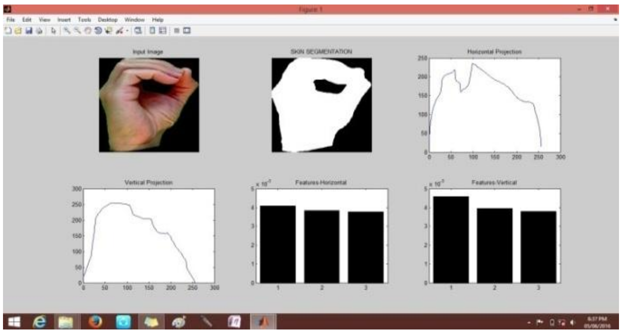

Fig. 4. The pre-processing result of the number '0'.

The three higher order moments are taken as the features of Fourier descriptor which show 6 graphs. Three features each for horizontal and vertical projection. The result shows first three and last graph has greater accuracy and uniform. The first side graph is of variance, next one skewness and last one kurtosis. The fig.5 shows the test graphs of statistical features.

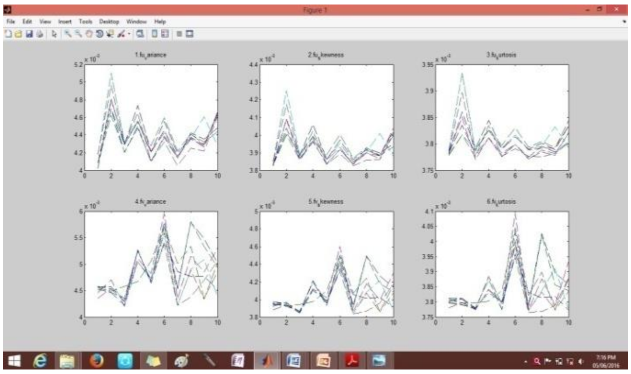

Fig. 5. Statistical feature graph showing features (Variance, Skewness, and kurtosis).

After creation of the feature vectors which are in .mat file format. These feature vectors are converted into the neurons i.e in terms of value and index of the features into 8x8 neuron map. Fig 6 depicts the representation of the SOM map in initial and trained state in terms of the various color blocks.

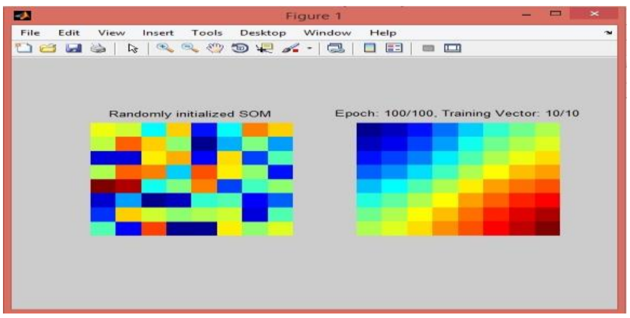

Fig 6: SOM neuron map (a)Randomly initialized SOM in terms of color. (b) Other shows the organized color display that runs for the SOM of 64 clusters and 100 epoch.

After SOM map creation the neuron map formed is grouped into cluster and then using euclidean distance and Hebb we get the desired class of the number.Finally the confusion matrix is plotted interms of computed vs desired gesture expressions. The Fig. 7 shows the plot of confusion matrix.

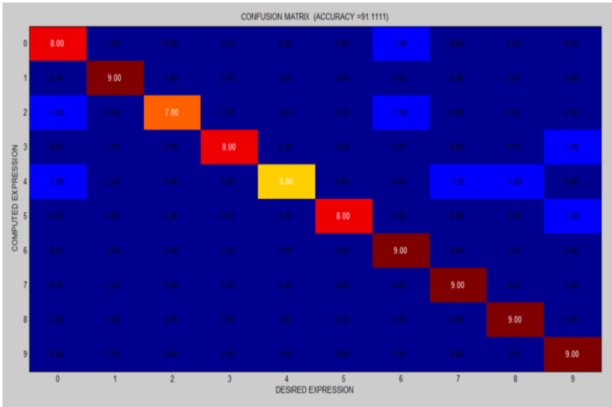

Fig. 7. Confusion Matrix of the recognized hand gesture system

The accuracy is calculated from confusion matrix which is described in Table I.

TABLE I. ACCURACY FROM CONFUSION MATRIX

Total hand sign.	**Recognition accuracy =** $\frac{\textbf{correct gestures}}{\textbf{Total number of gestures}}$ **. 100%**		
	Correctly identified	**Incorrect identified images**	**Accuracy**
10 hand sign X 9 dataset = 90	83	7	91.11%

The last step is the implementation of whole system in terms of the panel window for input, output, training and testing. Fig 8. Shows the GUI (Graphical user interface) for the hand sign of number '0'. The output is shown below with the display of the number '0'.

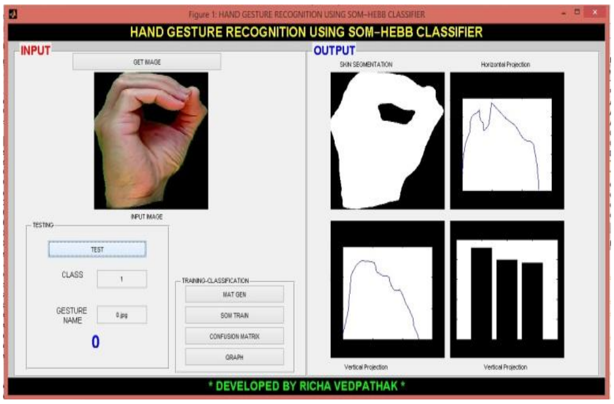

Fig. 8. Graphical User Interface for the hand gesture recognition result of the number "0".

V. CONCLUSION

The proposed system is based on static hand gesture recognition using SOM-Hebb classifier. The feature vectors obtained remain unchanged irrespective of position of image. It is not completely immune to rotation and scaling. The skin color segmentation is done using YCbCr color space into binary image along with filtering. Fourier descriptor is used for the feature extraction for features in terms of feature vector. The three central moments are used as features which have uniform distribution and helps in enhancing the accuracy. The SOM - Hebb used show proper category based identification. The SOM classifies on the basis neuron and cluster and Hebb with respect to class. The SOM classifier tends to get confused, while Hebb removes the confusion for identification of gesture. The training and testing is performed by both SOM and Hebb along with association with Euclidean distance. The Euclidean distance is used as secondary classifier. It is used to optimize and increase the accuracy of the system. The final output is analysed with the help of confusion matrix for analysing the true and false recognition. The whole system is implemented successfully on MATLAB. The system implemented show the accuracy of 91.11%. In future the system could be implemented using real time model based approach using camera.

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