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Comparison of Classification Techniques for Hand Gesture Recognition System

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ABSTRACT: Gesture recognition is useful means of communication between deaf or mute people with people who are unaware of sign language. Hand gesture is one of the type of gesture which uses single or two hands for conveying the gesture. The main applications of the hand gesture system are virtual reality, 3D gaming, and biometrics. Classification is the last and important step in the gesture recognition system. This paper discusses two types of minimum distance classifiers for the hand gesture recognition system. One classifier is based on the Self Organizing Maps (SOM) along with Hebbian network and other is the Euclidean distance classifier. The work is simulated in Matlab 2010a .The classifiers are compared in terms of their recognition accuracy. The recognition accuracy for SOM-Hebb classifier is 92.73 % and 82.05% for Euclidean distance classifier. The simulation results reveal that SOM-Hebb classifier outperforms the Euclidean distance classifier.

KEYWORDS: Classification, Euclidean distance, Hebb, Self Organizing Map (SOM), SOM-Hebb.

I. INTRODUCTION

The hand gesture system has well known application in the field of image processing, FPGA based and embedded systems. Gesture recognition is not only used to bridge the gap between normal and disabled people but also between human and computer by concept of human computer interface (HCI). HCI means a smart way of interaction of hand gestures in day to day life applications. Hand signs are of two categories one is static hand gesture and other is dynamic. Static are real or non- real time applications based and consider certain pose or sign without movement. Dynamic gesture is mainly used in real time applications. The dynamic gesture is further divided into local, global and local alongwith global. Dynamic gesture contains the movement of hand for particular period of time. Local dynamic comprises of finger movements, while global include movement of entire hand.

The hand gesture process undergoes many processes to get the input colored image of hand sign to be recognized in text or audio. The first phase includes of pre-processing includes resizing, conversion of image into gray scale or binary image, noise removal and converting into a variable. In feature extraction process, the features are extracted from the binary image value and converted into variable based on texture or shape feature. Feature extracted are used in form of statistical feature like entropy, variance, mean, standard deviation, higher order moments. These features form feature vector which are used classification. The last phase of recognition system is classification. The classification is process by which the processed image is easily recognized. It includes neural network classifier, fuzzy and expert system, minimum distance classifier.

II. RELATED WORK

The various classifier techniques have been reported for hand gesture recognition system. In [1] authors used SOM-Hebb hybrid network for classification and implemented it on FPGA. They used 24 letters American Sign Language (ASL) as input by using video processing technique using colored glove of red and white combination. The system is made robust by using perturbation and neuron culling. Authors used Indian Sign Language (ISL) as dataset with ANN (Artificial Neural Network) as a classifier. Fourier descriptor is used along with distance transform which consist of Euclidean distance and its types. The skin color segmentation needs filtering and morphological operator to remove unnecessary noise. The accuracy obtained was 91.11%. For feature extraction statistical features like variance, skewness and kurtosis is used which increases accuracy of the system in [3]. In [4] ISL is used a sign language and

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KSOFM or SOM (Kohonen Self Organizing Map) as classifier. The feature extraction is done using (DCT) Discrete Cosine Transform. The system is implemented using MATLAB which is not a complete sign language recognition system. The accuracy obtained is approximately 80%. The information of other body parts is necessary for the system. In [5] the authors compared two classifiers of Range Check Classifier (RC) and SOM –Hebb hybrid network classifier for hand sign recognition. The accuracy of SOM-Hebb and RC is 76.29% and 67.31%.The SOM-Hebb outperforms better than the RC by 9% in terms of accuracy. The Hybrid classifier is 2.6 times better than the RC classifier. The circuit size of RC is less as compared to SOM-Hebb. In [6] authors used the SOM-Hebb classifier for classification of 41 Japanese hand sign. The recognition rate of the system improved by 15%. In addition, results showed that the use of the shape of hand as the data had a large deviation for the training which had improved the recognition performance. In [10] the author compared the unsupervised self – organizing algorithm (SOM) with supervised learning neural network. The author concluded that error back-propagation learning algorithm is competent for many non- linear real time problems. On the other hand the classification of KSOM – the unsupervised model outperforms efficiently than the supervised learning algorithm. The approximate accuracy of KSOFM and back-propagation learning algorithm is 86 to 92% and 79 to 89%.

III. CLASSIFIERS

This section gives the comparison of SOM-Hebb and Euclidean distance classifier. Every classifier mainly comprises of the two phases namely training (learning phase) and testing phase (recall/comparison phase). The training phase includes the use of all processes of pre-processing, feature extraction and use of this feature as trained data. This trained data is used for classification purpose. Testing phase includes comparison and testing of the known or unknown class of gesture with trained data. The different classifiers are explained as follows:

A. *Self Organizing Maps(SOM)*

- SOM are known as Kohonen Self-Organizing Maps (or Self-Organizing Maps).It is a type of unsupervised single feedforward neural network. It was developed by Tuevo Kohonen. SOM learn on its own through unsupervised competitive learning. The topological relationships between input data are preserved when mapped to a SOM network.
- SOM works mainly on two modes: training and mapping. Training builds the map using input samples, while mapping automatically classifies a new input vector.
- A winner is calculated determining closest difference between input vector (input feature vector) with weight vector. Weight vector is the vector which is due to the connectivity between output and input layer of SOM neuron map.
- Mechanism is divided into 3 phases :
  A. **Competition:** In this step for each input pattern, winner and the closest neuron are found.
  B. **Cooperation:** In this phase winner is found but along with it the neighboring neurons are updated to be alike that of winning neuron. Gaussian neighborhood is generally used for neighborhood neuron updation.
  C. **Adaptation:** In last step, the winning neuron and its neighborhood neurons are enabled to increase their individual values by the function which is discriminated in relation to the input pattern through suitable synaptic weight adjusts with connection weights associated with it.

B. *SOM-Hebb Classifier*

SOM-Hebb is a hybrid classifier which uses combination of supervised and unsupervised neural network. Hebb is a supervised learning network and helps SOM to recognize the respective class of gesture. The feature vector is given as input to this network. SOM converts these vectors into equal dimension of neurons and trains (learns) and recall (updates) its map in form of cluster using its mechanism. The winner is found twice in this classifier firstly by SOM for formation of winner cluster and secondly by Hebb to find class of cluster based on the location, link count of the neuron to cluster and from cluster to class. The trained feature vector or trained learning data is compared with the winner from cluster .The synchronized strong link of the compared data gives the required class of the gesture. The architecture of SOM-Hebb classifier is shown in Fig 1. The final output for the recognized gesture is in the form audio and text. The audio file consists of the .wav file of all gestures while the text is displayed along with it in capital letters.

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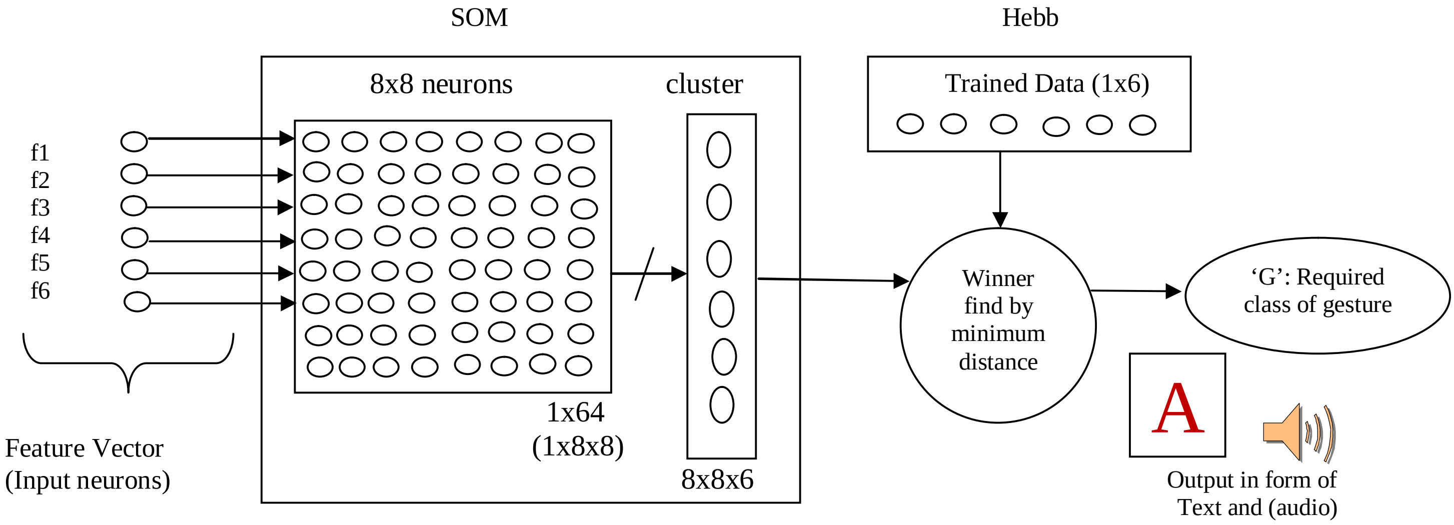

Fig.1.Architecture of the SOM-Hebb Classifier.

The flowchart in Fig. 2 describes the mechanism of the SOM-Hebb as a hybrid classifier through the flowchart. For training and testing in SOM-Hebb classifier, the SOM map is necessary. This map is converted into form of cluster value in form of association map from which class of gesture is found. The winner is found for all neurons one by one. But many times some neurons do not participate so Euclidean distance can be used.

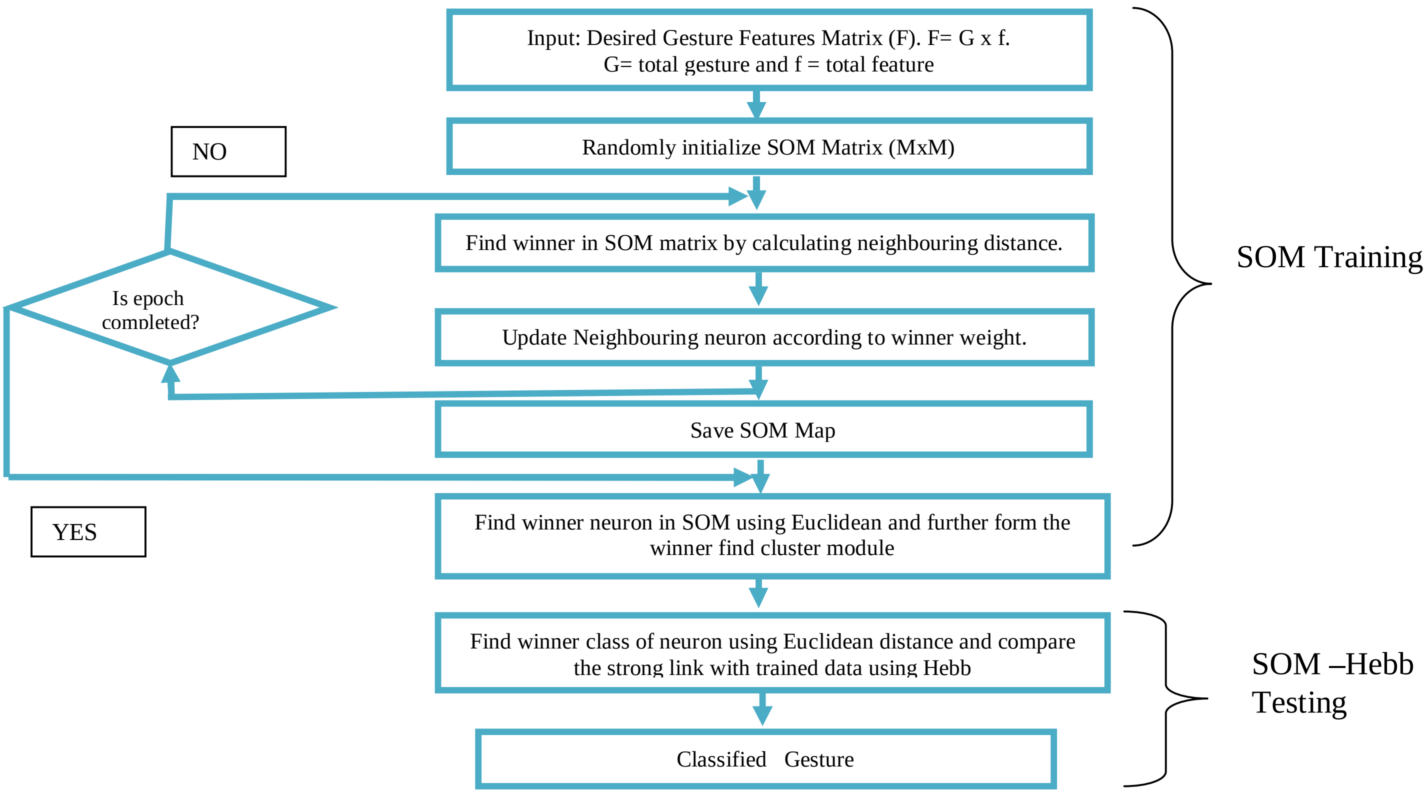

Fig.2.Flowchart of SOM-Hebb Classifier.

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Design of SOM-Hebb Classifier:

- Dimension size of the training feature vectors: (Features) Input Neurons = 6;
- Width of a square SOM map : n = MxM = 8x8 neurons;
- Number of epochs used for training =100;
- Number of training vectors that are generated =26(letters) X 6(features).
- Initial learning rate = 0.1;Exponential decay rate of the learning rate= 0.05;
- Initial variance of a Gaussian function that is used to determine the neighbors of the best matching unit (BMU):sgm0=20; Exponential decay rate of the Gaussian variance: sgmdecay= 0.05.
- Input to Hebb network = 1x64 neurons i.e. one cluster.
- Output of the classifier in terms: Class. Number of output classes: A-Z (26 letter gestures).

C. *Euclidean Distance Classifier.*

It is a minimum distance classifier. It checks the similarity between two points. The points can be pixel of image, feature vectors of different trained or test feature vector. It is a distance based classification method. The Euclidean distance classifier is invariant to rotation of the image. It is commonly used to measure for finding the distance transformation, but it involves time consuming calculations which consist of square, square root and the minimum over a set of floating numbers. The squared Euclidean distance transform is calculated by using a squared Euclidean distance structuring element. The distance transform of the image is widely used for object feature extraction and recognition tasks. The Euclidean distance is the square of difference between two points or two vectors i.e. training and testing vectors.

$$ED = d\,(p, q) = \sqrt[2]{(p1-q1)^2 + (p2-q2)^2} = |(\boldsymbol{p1}-\boldsymbol{q2}) + (\boldsymbol{p2}-\boldsymbol{q2})|\,, \qquad \text{Eq. (1)}$$

ED is the Euclidean distance vector, where p, q are the two values of the vectors i, j, where i, j= 1, 2 which symbolizes testing and training vectors. The minimum distance of the Euclidean distance vector is considered as correct class or hand sign position vector. Fig.4. shows the flowchart of the Euclidean distance classifier. The main difference between SOM-Hebb and Euclidean is that SOM-Hebb requires SOM map for training and testing along with Hebb and Euclidean distance. SOM-Hebb requires untrained data and SOM map which on further process form association map by Hebb and finally the class of gesture is found. While in case of Euclidean distance average of all the records of feature vector and input gesture which are depicted as training data and test data.

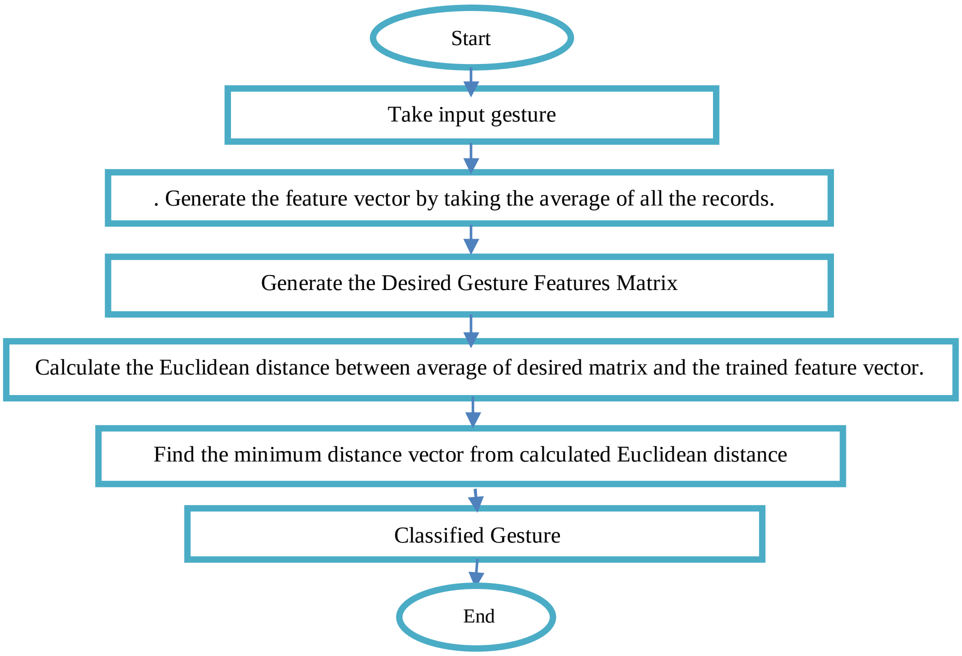

Fig.3.Flowchart of Euclidean Distance Classifier

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IV. EXPERIMENTAL RESULTS

The hand gesture recognition algorithm is implemented using MATLAB 2010a.The simulation result involves the comparison of the SOM-Hebb and Euclidean distance classifier in terms of recognition accuracy by using confusion matrix. The pre-processing was done using YCbCr color space to binary, feature extraction was done using Fourier descriptor and statistical feature like variance, skewness and kurtosis. The inputs to the hand gesture system consist of 26 letters from A-Z which are taken from Massey University. Confusion matrix is a matrix which is used for calculation of recognition accuracy. It is plot of the desired gesture expressions against the calculated gesture expressions. The diagonal element represents the correctly recognized gestures. The elements offside the diagonal are the confused or wrongly recognized results. The confusion matrix of SOM-Hebb classifiers as shown in Fig.4 in which the three letters are more confused namely ‘A’, ‘K’ and ‘L’. Similarly the confusion matrix of Euclidean Classifier as shown in Fig.5 depicts more confused gesture letters namely ‘B’, ‘C’, ‘D’, ‘M’, ‘Q’, ‘Y’ than rest letters.

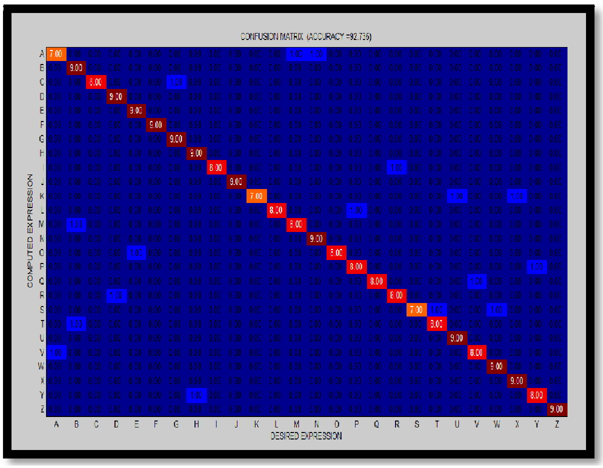

Fig 4. Confusion matrix of SOM-Hebb for 26 letters.

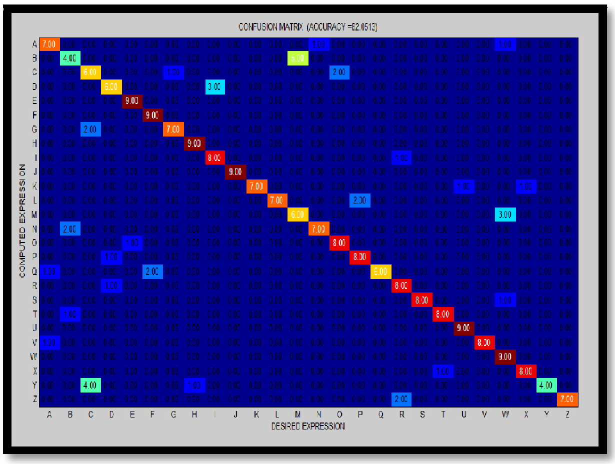

Fig 5. Confusion matrix of Euclidean Distance for 26 letters

The recognition accuracy of the SOM-Hebb and Euclidean distance is calculated by formula given below with reference to confusion matrix:

$$\textbf{Recognition accuracy} = \frac{Number\ of\ Correctly\ \ recognized\ \ \ gestures}{Total\ number\ of\ gestures} . 100\%$$

The total hand signs are calculated as 26 hand sign X 9 dataset = 234. The SOM-Hebb has 217 diagonally arranged correct gestures and 17 incorrect gestures which are incorrect and scattered one. Similarly for the Euclidean distance classifier 192 correct gesture and 42 incorrect one. The Table I summarizes the performance of the SOM-Hebb and Euclidean distance classifier in terms of recognition accuracy.

TABLE I: COMPARISON OF THE CLASSIFER BASED ON RECOGNITION ACCURACY.

Classifier	Correctly identified	Incorrect identified images	Accuracy
SOM-Hebb	217	17	92.73%
Euclidean Distance	192	42	82.05%

The SOM-Hebb surpasses the performance of the Euclidean distance classifier by 10.72%.

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V. CONCLUSION AND FUTURE WORK

The simulation results show that SOM-Hebb classifier algorithm performs better than Euclidean distance classifier. The SOM-Hebb provides 10.72 % increase in recognition accuracy as compared to Euclidean distance classifier. On the other hand Euclidean distance classifier is insensitive to illumination and not immune to rotation of the images. The performance of the SOM-Hebb classifier can be further improved if the Euclidean distance is used along with it. SOM-Hebb classifier also uses Euclidean distance for finding minimum distance of neuron in the form of winner. The performance of the classifier of the Euclidean distance can be further enhanced by using Eigen weighted Euclidean distance and chess board distance in future as compared to conventional Euclidean distance classifier.

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BIOGRAPHY

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