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Performance Analysis and comparison of Recurrent Network for Pattern Storage and Recalling of Static Images

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ABSTRACT

Pattern storage and recalling is a problem of interest in field of pattern recognition till now, which is used to mimic the human brain. Auto associative memory is an extensively used network for pattern storage and recalling of patterns. Recurrent network like Hopfield is popularly known auto associative memory networks. In this paper we present performance analysis and comparison analysis in term of storage and recalling efficiency of Hopfield network. Our analysis is based on the storage capacity and recalled efficiency of the pattern storage network for original images as well as distorted form of these images. For storage and recalling, edge Dilation and SOM are the methods for feature extraction used here to evaluate the performance of pattern storage network.

Keywords: Hopfield Neural Network, Pattern Recognition, Recurrent network,

I. INTRODUCTION

A Recurrent Neural Network (RNN) is a distinct class of Artificial Neural Networks (ANNs) that can be used to process arbitrary sequences of inputs. RNNs are widely being used for pattern recognition task, because pattern recognition mainly depends on pattern storage and pattern recalling. There are numerous machine learning methods which have been used for pattern storage and retrieval. But, RNN has gained its own place due to its wide applicability. Most widely used RNNs include Hopfield networks used to model the understanding of human memory, though Hopfield networks were not designed to process sequences of patterns [1, 2]. Stochastic RNN based Boltzmann machine which is supposed to be a Monte Carlo version of Hopfield networks is used to solve combinatorial problems. The results are elaborated in this paper. We have used weight matrix calculation method. We have used the weight adjustment algorithm.

Hopfield Neural Network [1] has characteristic feature of dynamic feedback system. So the output of a direct operation serves as an input for the next operation of a network as shown in Fig 1.These networks do not impact the network's ability to act as a content-addressable associative memory system and have the capability to initiate the retrieval of the most coherent behavior vector in the neural network. Both the auto-association and hetero-association operations happen together. The network system represents a stable behavior and converges at the single motionless point. When this point becomes an input to a dynamic system, we will have a motionless point as the output. This property helps the system to maintain a stable state.

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Periodic cycles may occur in RNNs due to asymmetric weights and the network system may exhibit chaotic behavior. This behavior is not generalized and it is limited to a relatively small segment of the phase space. It has no negative impact on the network's ability to act as an associative array.

A Hopfield neural network can retrieve any of the learned patterns just by an exposure to only partial information about the learned pattern. The Hopfield network has a tendency of stable pattern recognition similar to human brain, usually, if there is more than one fixed point. The selection of starting point for the initial iteration has a great effect on the network convergence [3]. The motionless points in the network are called attractors. The vectors which are attracted to a particular attractor during the iterations represent the "attraction area" or "attraction basin" of that attractor. The set of these motionless points of Hopfield's network acts as a memory. Such a network operates as an associative memory [4]. The input vectors entering to the sphere of attraction of some another attractor also gets connected to it. For example, a desirable image acts as an attractor, then the area of attraction can be consisting of incomplete versions of this image. In such a case there are good chances that images that vaguely recall to a desirable image may be remembered by the network associated with this image.

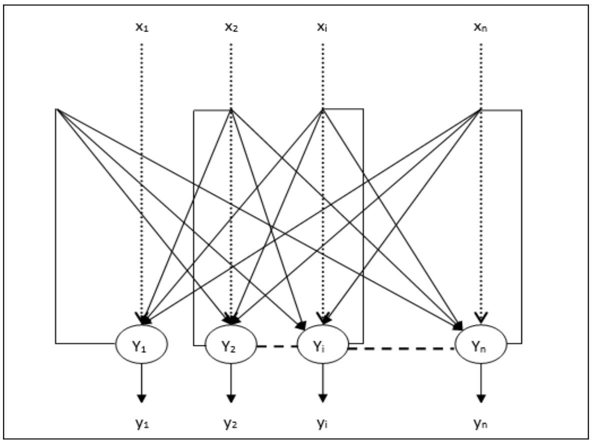

Fig 1: Architecture of Binary Hopfield neural network

A discrete Hopfield networks with binary bipolar input and output pattern shown above in fig 1. The weight matrix of integers which is symmetric by nature is represented by W =$||w_{ij}||$. The diagonal element of the weight matrix is set to zero. Conventional matrix with multiplication is used to multiply the input vector X to a input weight matrix W. for each input pattern X, the output pattern is calculated by feeding X to the corresponding neurons in HNN. For asynchronous update, only one component of output pattern Y = $[y_j]$, is used. This component is selected either randomly or by turn and pass to a threshold function for which output is bipolar (–1, or +1), which replace the corresponding component in input vector to form new input vector for next iteration. The termination of this update process take place when all input and output vectors become same. This is the achievement of motionless point.

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II, ALGORITHM OF RECALL USING ASYNCHRONOUS UPDATES

At beginning an input vector X and weight matrix $||w_{ij}||$ are applied to input neurons. It identifies the total input signal at the j^{th} neuron as $y_{inj}(x)$ and gets the outputs. These outputs of the neurons are worked as inputs for new iteration by applying the following operations:

Components of an output vector y_j,

$$y_j = F(\sum_{i=1}^{n} w_{ij} x_i) \qquad (1)$$

Where

$j = 1, 2, ..., n$

$$F(x) = \begin{Bmatrix} -1 & \text{if} x < 0 \\ 1 & \text{if} x > 0 \\ & y \text{previous} \text{if} x = 0 \end{Bmatrix}$$

For asynchronous correction, i.e. [2–4]:

Step 1: to start the algorithm, define an input vector

$(x_1; x_2; ...; x_n)$

Step 2: Calculate y_j by eq. (1).

Step 3: replace component x1 by y1 in input vector

$(x_1\ x_2; ...; x_n)$ as $(y_1; x_1; x_2; ...; x_n) = Y$ and a feed Y back to input X.

. Step 4: this process will continue to find y_2; y_3, etc. and replace the corresponding input components.

Repeat steps 2 and 3 until the vector: $Y = (y_1; y_2; ...; y_n)$ ceases to change.

Calculate the value of communications energy E if at least one of outputs has changed:

$$E = 1/2 \sum_{i=1}^{n} . \sum_{j=1}^{n} w_{ij} x_i x_j (2)$$

The vector will convey convergence to a motionless point if the energy E reduces. Zeros on a main diagonal of a weight matrix W and asynchronous update guarantee that the energy function (2) will decrease with each step [2, 5]. To ensure the convergence to a motionless point an asynchronous up dating is inevitable. In place of a motionless point a network with periodic cycle can be developed as terminal state of an attractor if we permit the input vector to get corrected in iteration.

III. FEATURE EXTRACTION

Feature extraction is an important step in the design of a sample organization. Its main goal is to extract the appropriate information to characterize each class. Feature extraction techniques support a variety of image processing applications. The characteristics describe the behavior of an image; they give you an idea of their position in terms of storage space, efficiency in classification and time use [6, 7]. The self-organizing map is an artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional representation of the training patterns while retaining the topological characteristics of the input space. A self-organizing map consists of a single-layered feed-forward network in which the outputs are arranged in the low-dimensional grid. Each input is connected to all output neurons. A weighting vector of the same dimension as the input vectors is attached to each neuron. The adaptation (training) algorithm uses competitive learning [8].

The edge detection is a kind of image segmentation techniques that determine the presence of an edge or a line in an image and suitably outline it. The main cause of edge detection is to simplify the image data to minimize the data to be processed [9, 10]. The Fast Fourier Transform is a computational tool that facilitates signal

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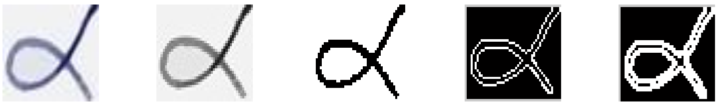
analysis and filter simulation using digital computers. In this paper we have taken 10 images of Greek symbol as shown in figure 2. The different steps for preprocessing task in the Edge dilation method are shown in figure 3.

Fig 2: Static images of 10 Greek symbols.

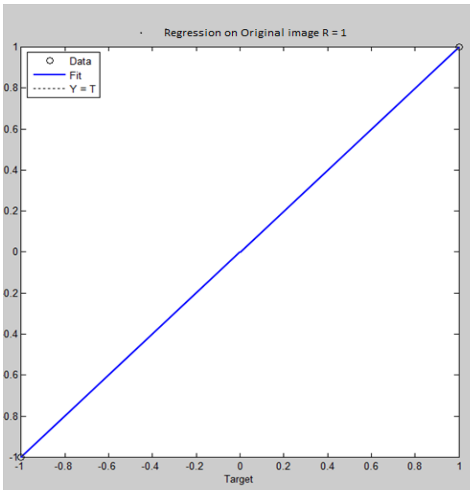


RGB image	Gray image	Binary image	Edge of image	Dilation of image

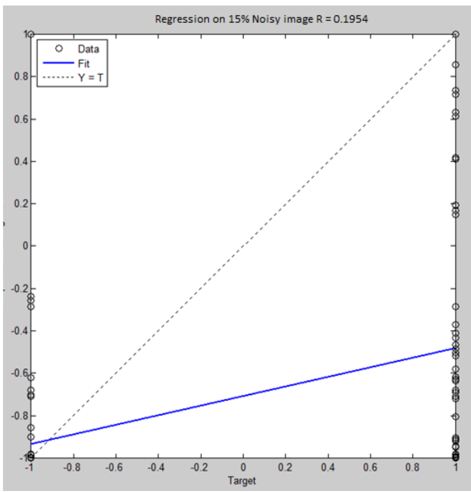
Fig 3: Various stages of image processing for extracting features

IV. ANALYSIS OF RESULT

In this experiment the input stimuli for SOM network is presented in preprocessed form. We have taken features for SOM via ED and FFT method of feature extraction. This pattern information of static images is passed in HNN of 900 processing units. The pattern information in preprocessed form of static images is presented to SOM network of 15 × 15 neighboring region. The SOM network produces a codebook for each method which is used as pattern information for Hopfield Neural Network. The performance of recalling for the feature map of original static images and erroneous images is presented in figure 4 for ED preprocessed features and in figure 5 for FFT preprocessed features respectively.



a



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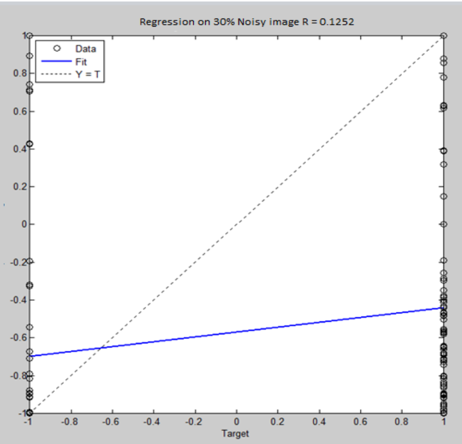

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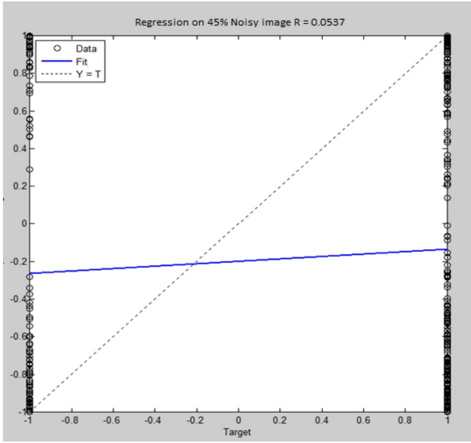

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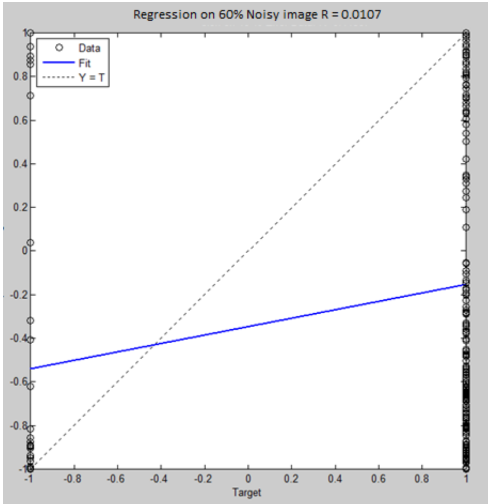
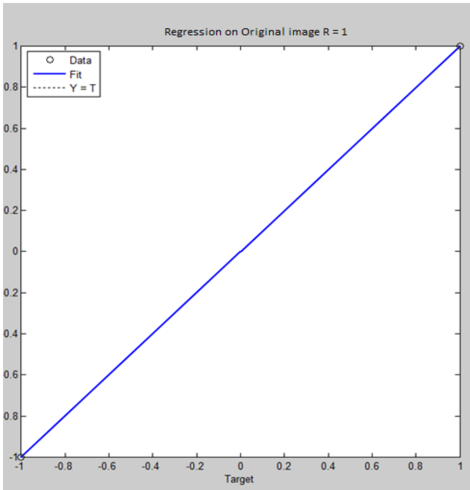
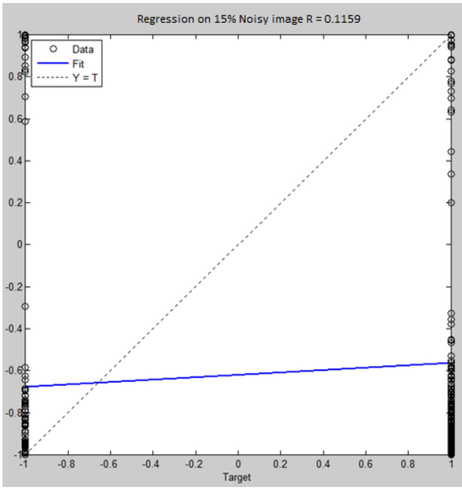


e

Fig 4: Regression line preprocessed from ED method. **(a).** For original image, **(b).** For 15 % error image, **(c).** For 30 % error image, **(d).** For 45 % error image, **(e).** For 60 % error image,



a



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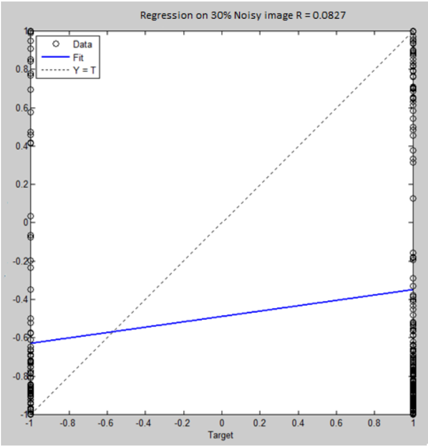

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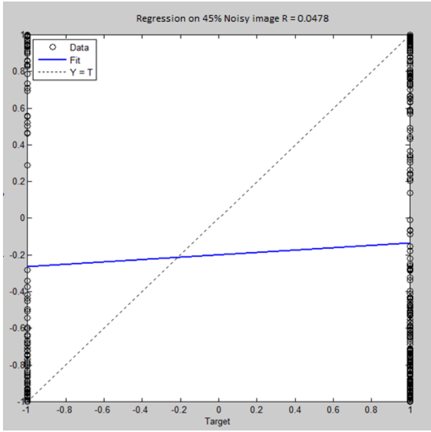

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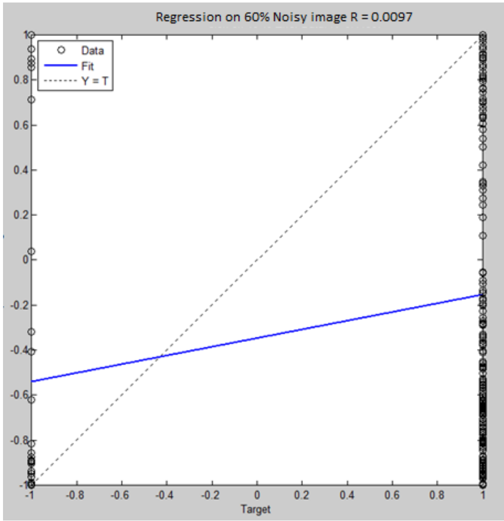

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Fig 5: Regression line preprocessed from FFT method. **(a)**. For original image , **(b).** For 15 % error image, **(c.)** for 30 % error image, **(d).** For 45 % error image, **(e)** For 60 % error image.

The Result of above regression line can be summarized as shown in below table no 1. The same is also shown in graphical form via chart in figure 6.

Table 1. Performance Evaluation of Hopfield Neural Network for recalling using SOM method with ED and FFT.

Methodology used	Original image	15% Error	30% Error	45% Error	60% Error
Regression R of SOM using ED	1	0.1954	0.1252	0.0537	0.0107
Regression R of SOM using FFT	1	0.1159	0.0827	0.0478	0.0097

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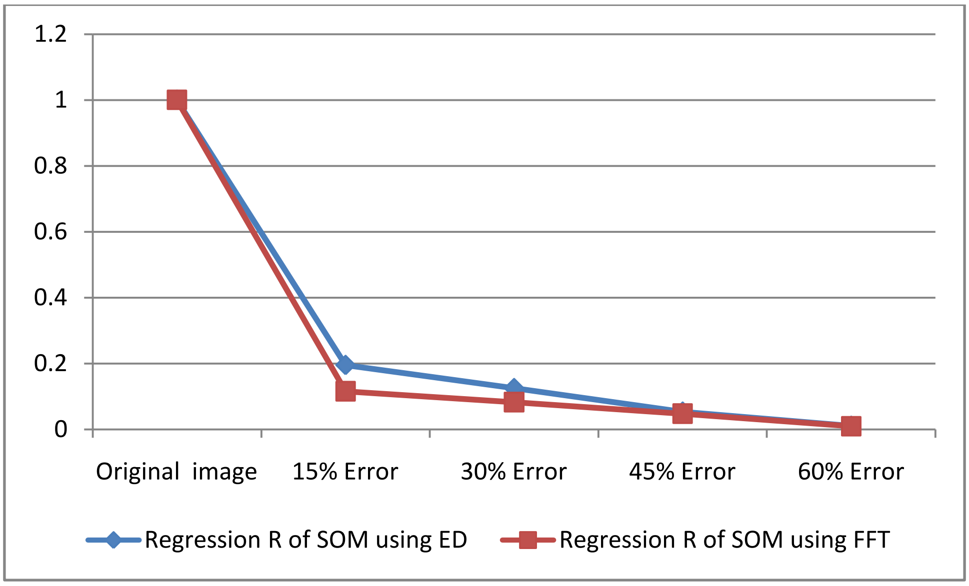

Fig 6: Regression line in graphical form for Performance of Hopfield neural network for SOM with ED and FFT feature method for recalling.

V. CONCLUSION

It has been observed that since the error in original images is 30% and above, the performance of the callback decreases rapidly. The experiments carried out in the present study were tested with two feature extraction methods, namely Edge Dilation (ED) and Self Organizing Map (SOM). The hybrid learning rule has been proposed to improve the storage and retrieval efficiency of the Hopfield network. The performance of Hopfield network is better when the prototype samples presented to it are filtered by ED methods. The proposed hybrid learning rule with considered feature extraction methods was used to evaluate the performance of Hopfield's neural network for static original images and their defective or erroneous images.

The SOM was also performed with same efficiency and accuracy as the FFT and ED was performing in recalling process but the poor performance of SOM is exhibit for noisy images with respect to other two methods. The performance of SOM for preprocessed stimuli with ED exhibit more accuracy in recalling in comparison to SOM with FFT. The performance of ED using SOM to prepare feature for pattern information and storage in Hopfield Neural Network then recalling is found much better over the methods.

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