IMAGE STORAGE AND RETRIEVAL IN GRADED MEMORY

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ABSTRACT
A new storage and retrieval methodology which is similar to human memory (which we call it as graded memory) for picture images is explored using multilayer Hopfield neural network The graded memory uses multilayer Hopfield neural network for storing the picture information in some pre-defined resolution. During the data retrieval operation, down sampled image is provided to the graded memory. The graded memory first gives out some coarse output, later the finer details may be synthesized based on the coarse output. The memory starts giving out more and more accurate output with lapse of time, as more and more resolution in the output is requested.

KEYWORDS: *Hopfield network, graded memory*

I. INTRODUCTION

Recent trends show that many applications use information in the form of picture or video requiring one to store this information on a storage device in some form. Also, many applications do not need high resolution picture to arrive at a conclusion. If the situation warrants, one can ask for the picture with higher resolution

This paper evaluates use of multilayer Hopfield neural network as a method of storing an image in a predefined resolution. The generation of data with more and more resolution from the coarse data which is available at first hand is also analysed.This multi resolution property is used in graded memory, where, the image quality in a stored image increases with lapse of time, if one can afford to wait for sufficiently long time. Compact storage and online generation of the multi resolution components are the essence of this concept.

Multilayer neural network with multi valued neurons are used in classifying textures is presented in [12]. There are many approaches in the literature storing static images with gray scale. These are mainly associated with binary associative memories. Generally, binary associative memories use activation function with two states. Developing an efficient memory storing a gray scale image with L gray levels and n (n = MxN), the number of pixels is really a complex problem to deal with. Since, during a recall of the image, the recalled image might be different in any of the n pixels. To store such an image in a binary associative memory, it requires, total of nL neurons. This kind of network in fully connected fashion will have n^2L^2 connections which is practically impossible to simulate for an image with more number of pixels or to design the hardware for the same.

Few authors have proposed methods to reduce the time complexity using neural networks with complex-valued neurons [1-3] wherein, each neuron can take any of the values out of 2^L values equally spaced on the unit circle. In this case, each gray level corresponds to a particular phase value. As there are n pixels, only n neurons are needed with n^2 connections. They have demonstrated that gray-scale images can be stored and recalled using such network as long as the phase shift between gray pattern components is maintained.

The two-dimensional cellular neural network (CNN) is of size MxN where, M is is the number of rows and N is the number of columns. C(i,j) represents a cell located at i^{th} row and j^{th} column. The detailed theory on cellular neural networks is presented in [4]. The work [5,6] propose neural networks consisting of multi-level states for each neuron. The activation function has 2^L plateaus instead of two as in normal sigmoid function. Each state of the multi-valued states of the neuron corresponds to the gray levels. The extensive details on how to generalize fully connected Hopfield neural network is presented in [7]. This is done by replacing two-level activation function with multi-level activation functions. It has been shown that activation function having N+ 1 level gives N+1 minima and N saddle points.

Gray-scale Image recall from Hopfield multilayer neural network by providing noisy image is presented in [8]. The algorithm and digital implementation of the algorithm to carry out image recall is provided in [9]. The multilayer Hopfield network with intra layer connections only for recalling an image is presented in [10]. All these works mainly target at recalling an image by providing a noisy version of the image.

The method presented in [10] decomposes the image into L binary patterns. Each pattern represents one bit in a digital coding of the gray levels. The image is stored independently using a conventional neural binary network with n neurons, where n is the number of pixels. There are L uncoupled neural networks with n^2 connections in each level. The main advantage is that L uncoupled neural networks can be implemented in parallel saving considerable amount of time during both training as well as recall. In this method, if a binary pattern cannot be stored in one sub-network, then the whole image cannot be stored. Same thing applies to image recall.

The paper is organized as follows. Section II briefly describes multilayer Hopfield neural network with basic state equations. The proposed architecture and design of graded memory is discussed in section III. Section IV is dedicated to simulation and results along with the simulation setup. Conclusion and future scope of work is discussed in section V.

II. HOPFIELD NEURAL NETWORK

Multilayer 2-dimensional Hopfield neural network [11] has only one layer of neurons. Each neuron has an input, an output and also performs computation. All neurons in the layer have bidirectional interconnections. The state equation of the network is given by

$$\frac{dU_{ij}}{dt} = -U_{ij} + \sum_{kl} W_{ij,kl}V_{kl} + I_{ij} \qquad (1)$$

Where i, k = 0,1,2 …M and j, l = 0,1,2…N

MxN is the number of neurons, U_{ij} is the input to the neuron at i^{th} row and j^{th} column. V_{kl} is the neuron output at i^{th} row and j^{th} column. W = [$W_{ij,kl}$] is the weight matrix for connections. Input bias I_{ij} is taken as zero for all i, j here. The output Vij is found by applying saturation function f(x) = 0.5(|x+1|-|x-1|).

In this work, to store a gray scale image, 3-dimensional (MxNxL) multilayer Hopfield neural network is considered, where M denotes row, N column and L the level. In the grid of 3-dimensional neurons, the current neuron is denoted by C(i,j,p) where i, j, p denote row, column and level respectively. Each neuron is connected to other neurons in the neighbourhood as defined in [8].

The state equation for this 3-dimensional Hopfield neural network having L number of 2-dimensional layers is given by

$$\frac{dU_{ijp}}{dt} = -U_{ijp} + \sum_{C(k,l,q)\in N_{r,s}(i,j,p)} W_{ijp,klq}V_{klq} + I_{ijp} \qquad (2)$$

The image is decomposed into binary patterns using binary weighted code. These are then converted to bipolar patterns and these bipolar patterns are used to train the neural network. . It is observed that binary patterns coded in reflective gray coding technique did not give better results compared to, when binary patterns coded using binary weighted code. Whereas, in [8] binary patterns are coded in reflective gray coding technique to reduce the effect of noise on the neural network during image retrieval.

III. DESIGN OF GRADED MEMORY

The architecture of graded memory is as shown in figure 1.

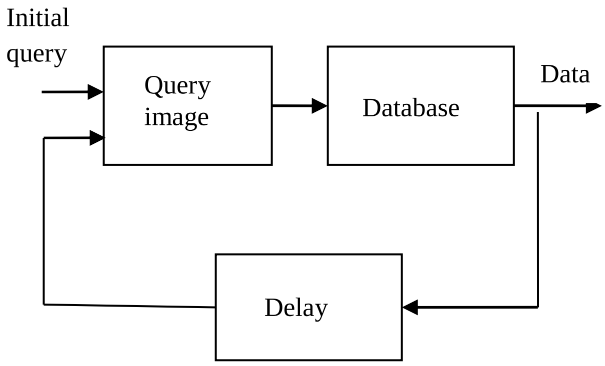


Figure 1 Proposed Graded memory architecture

The multilayer Hopfield neural network stores multiple images in some predefined resolution in other words, it contains database of images to be queried. These images are stored during training of the neural network. When the down sample version of any of the images stored in the neural network is provided as query image. The network first gives out some coarse output. This coarse output is again fed back to the neural network as the query image, in this case the network again gives an output which is better than the one it gave before. This process is repeated till the output image has sufficient information to arrive at conclusion.

The network also provides high resolution image when the query image is of low resolution. To store the gray-scale image in a memory, the image LENA.jpg of size as shown figure 2 is taken, since storing a 128x128 sized gray-scale image requires large number of neurons and connections requiring huge computer resources. Due to computer resource issues related to virtual memory allotment for storing large number of connections, the gray-scale image to be stored is partitioned into many sub-blocks of equal size.

Figure 2 LENA image used for training the neural network

The algorithm used to train the neural network is adapted from [8]. Whereas in [8], they use symmetric connection matrix, but, here the connection matrix W is not symmetric, constraint not being used and the learning rate taken as equal to 1.

IV. SIMULATION AND RESULTS

The simulation is setup using MATLAB 7.10. The Matlab code is written to simulate the multilayer Hopfield neural network. The LENA image is taken and resized to 32x32. This image is partitioned into 4 images each of size 16x16. The multilayer Hopfield neural network is trained to store these 4 portioned images. Once the training is completed, the connection matrix W is fixed. During the data retrieval phase, these 4 partitioned images are down sampled to 8x8 and applied as query inputs one after the other and the corresponding output images are combined to get the first pass image of size 32x32. The output image thus obtained is the coarse output which may not match exactly pixel to pixel. To get the better output, the output thus obtained is fed back as the query input and the corresponding output images are combined to get the second level output image which is better than the coarse output that was retrieved in first pass. This process of feeding back the previously retrieved output and getting the better output in the current retrieval is repeated until the image quality is satisfactory.

The results for the LENA image when partitioned into 4 sub-images and 9 sub-images are captured and shown in the tables 1- 3. The simulation of training and testing the multilayer Hopfield Neural network is done using MATLAB 7.10. During testing, to get the first level of down sampled version of the image, the pixel values of every alternate rows and columns of the training image are made zeros. The second level of down sampled image is got by making pixel values of 3 rows and columns zeros out of 4 rows and columns, to get the third level of down sampled image, pixel values of 7 rows and columns are made zeros out of 8 rows and columns.

The table 1 shows the results obtained when the network is trained for single LENA image of size 16x16 and also for 32x32. After training the network for the images of these sizes separately, the down sampled version of the image(alternate rows and columns made as zeros) is provided as the test image, it is observed that the network is able to recall the original image perfectly.

Table 2 shows the results obtained when network is trained for 4 images of size 16x16 as well as for 4 images of 32x32. The combined output image perfectly matches with the trained input in both these cases in one pass itself.

Table 3 shows the results obtained when the neural network is trained simultaneously for 9 images of size 16x16.

When the down sampled images are provided during testing, the network initially provides a coarse output with PSNR of 15.2736. This coarse output is fed as the input to the neural network to get an image of better quality with PSNR 17.5069. Again the image thus obtained is fed back to the neural network input to get an image with PSNR 21.4161 in third pass. This image is fed as the input to the neural network to get an image which perfectly matches with the trained image. It is observed that the network is able to provide better and better quality of image with the lapse of time in few iterations.

Table 1 Sets of single training image, testing image and corresponding output of the neural network

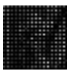
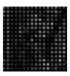
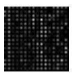
Sl No	Training image		Testing Image		Output of neural n/w		Remark
1	16x16		Down sampled to 4x4		16x16		Training image and output images both match
2	16x16		Down sampled to 8x8		16x16		Training image and output images both match
3	16x16 Down sampled to 8x8		Down sampled to 4x4		8x8		Training image and output images both match
4	32x32		Down sampled to 16x16		32x32		Training image and output images both match
5	32x32		Down sampled to 8x8		32x32		Training image and output images both match
6	32x32		Down sampled to 4x4		32x32		Training image and output images both match

Table 2 Sets of four training images, testing images and corresponding combined output of the neural network

Sl No	Training image		Testing Image		Output of neural n/w		Remark
1	32x32 image Down sampled to 16x16 = 4 images of 8x8		Down sampled 8x8 = 4 images 4x4		16x16		Training image and output images both match

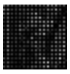
2	32x32= 16x16x 4 images		Down sampled 16x16 = 4 images of 8x8		32x32		Training image and output images both match
3	64x64 = 4 images of 32x32		Down sampled version of training image		64x64		Training image and output images both match

Table 3 Nine images of size 16x16 to get overall image of size 48x48 Testing image is down sampled version of the training image.

Training input	Testing input	Output	MSE	RMSE	PSNR(dB)
 1st pass	 Down sampled image		1.9459e+003	44.1123	15.2736
2nd pass			1.1636e+003	34.1111	17.5069
3rd pass			473.0130	21.7489	21.4161
4th pass			Training image and output images both match. PSNR is infinity		

V. CONCLUSION AND FUTURE WORK

Here the multilayer Hopfield neural network has been taken and analysed the possibility of using the network as a graded memory which gives out better and better output if one can afford to wait for sufficiently long time. The results indicate that one can store successfully nine images of size 16x16 and get back the original image in few passes when provided with the down sampled version of the trained images.

In our future work, we are going to test the concept of graded memory using one more image other than LENA. We are going to vary neighborhood parameters r and sas specified in [8] to see the effect on the image recall. Also in [8], they use Hopfield network connected in torus fashion. We would like to make this network as non-torus and study the effect on image recall.

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