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Image Reconstruction Using Generalized Hebbain Algorithm

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ABSTRACT: Digital image compression is an art and science for reducing the amount of data required to represent an image. It is the most useful and commercially successful technologies in the field of image processing to remove the irrelevant and redundant data from the image in order to be able to store or transmit data in an efficient manner.

This paper describes a method to compress the image using Generalized Hebbian Algorithm (GHA). It is a feed forward back propagation neural network method based on principle component analysis (PCA).

The performance of the above said technique is tested on a 512×512 grey scale Lena image. Simulation results show lower Mean Square error (MSE) & larger peak signal-to-noise ratio (PSNR), thus resulting in a better compression of the image without much affecting the image details.

Keywords: Digital Image Compression, Generalized Hebbain Algorithm (GHA), principle component analysis (PCA), Mean Square error (MSE), Peak signal-to-noise ratio (PSNR).

I. INTRODUCTION

Image compression plays a vital role in various applications. Uncompressed images require large storage space and high transmission bandwidth. The recent development in the web applications has urged the need for the technique which can compress the data without much affecting the original details. Image compression aims to remove the irrelevant and redundant data from the image in order to reconstruct a new image which could be stored or transmitted in an efficient manner. There are mainly two types of image compression techniques one is lossy and another lossless. The lossless technique is applicable in medical fields for MRI scans, ECG, X-ray etc. where every bit of the data is very essential. But for other applications where detailing of the image is not necessary, lossy technique can be used. For such type of compression, techniques like Generalized Hebbian Algorithm, Eigen Decomposition, cosine transform, etc. are very effective. These techniques give better results with small amount of data loss. They process the data in serial manner and hence require more computational time. This paper deals with an image compression technique using Generalized Hebbian Algorithm (GHA). It is Principal component neural network technique (PCNN) which organises itself to extract the principal components from the image data for compression. GHA is a linear feed forward neural network model for unsupervised learning with applications primarily in principal components analysis. The performance of the above said technique is tested on MATLAB for a 512×512 grey scale image. The reconstructed image has a lower MSE & larger PSNR which results in a better image quality and compression.

II. PRINCIPAL COMPONENT ANALYSIS (PCA)

This technique was developed by Person and Hotelling. It is also known as Karhunen-Loeve (KL) Transform. It deals with explaining the variance-covariance structure of the data through a few linear combinations of the original data. The general objective is data reduction and interpretation. PCA is an analytical approach that linearly transforms an original data into smaller set of uncorrelated data that contains at most information from the original data.

PCA finds the principal components of the dataset. It transfers the data into a new, lower-dimensional subspace into a new coordinate system. The first axis is the first principal component which is the component that explains greatest amount of variance in the data. The second principal component must be orthogonal to the first principal component. It does its best to capture the variance in the data that is not been captured in the first principal component in the first coordinate axis. The principal components are the eigenvectors of the covariance matrix of the original dataset. The PC's corresponds to the direction with greatest variance in the data.

III. GENERALIZED HEBBAIN ALGORITHM

The Generalized Hebbian Algorithm (GHA), also known in the literature as Sanger's rule. It is a linear feed forward neural network model for unsupervised learning with applications primarily in principal components analysis. The GHA tunes a Hebbian layer so that its weights form ordered principal components. The PC's are the basis vectors that are aligned such that the greatest variance by any projection lies on the first principal component. Consider a simple network which consists of single linear neuron as shown in figure 1.

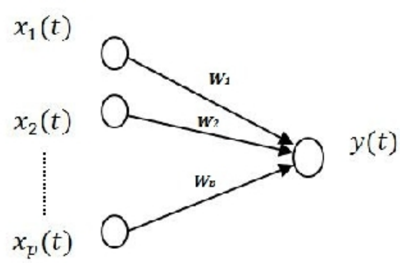

Fig. 1. Single linear neuronal model for GHA.

Hebbian learning provides a neural framework. In hebbian learning a single time dependent output neuron y(t) which dynamically modifies its firing rate at time t. The resulting output y is defined by,

$y = \sum_{i=1}^{m} w_i x_i$ ……………………………………(1)

According to Hebb postulate a synaptic weight w_i, varies with time and grows stronger when presynaptic signal x_i and postsynaptic signal coincide with postsynaptic signal.

$w_i(t+1) = w_i(t) + \eta y(t) x_i(t)$ ...………………...(2)

where, $i = 1,2, \dots, p$

Here, t denotes discrete time, $x_i(t)$ is input vector and η is learning-rate parameter. If limit is not set w increases to infinity. Hence this learning rule leads to unlimited growth of the synaptic weight w_i.To overcome this problem, Hebb rule was modified. Oja proposed new learning rule by adding term called multiplicative weight-decay. We can write

$w_i(t+1) = w_i(t) + \eta y(t)[x_i(t) - y(t) w_i(t)]$…..(3)

From the learning rule we normalize the weight vector and cause to converge to the eigen vector of the covariance matrix. We extract the first principal component. This rule only works for single linear output neuron. To understand more components, more outputs are necessary. Sanger introduced the Generalized Hebbian Algorithm which can accommodate more outputs. This is known as sanger's rule. Sanger than expanded the single neuronal model to a feed forward network with a single layer of linear neurons. Consider the feed forward network shown in figure 2.

The network consists of p inputs and one output. Each neuron in the output layer of the network is linear. The set of synaptic weights w_{ij} connecting source nodes i in the input layer to computation nodes j in the output layer, where $i = 1,2, \dots. p$ and $j = 1,2, \dots, l$. The output $y_{j(t)}$ of neuron j at time t, produced in response to the set of inputs is given by

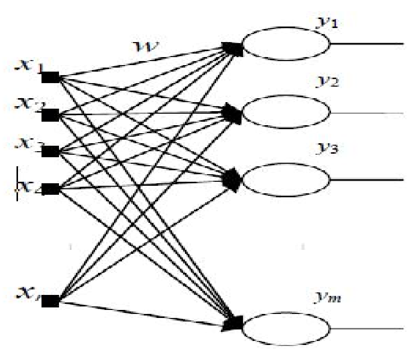

Fig. 2. Single layer neuronal models with feed forward network [8].

$$y_j(t) = \sum_{i=1}^{p} w_{ji}(t)x_i(t) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4)$$

Where $x_i(t)$ i^{th} component of the p-by-1 input vector and l is the desired number of principal components.

The synaptic weight $w_{ji}(t)$ is adapted in accordance with generalized form of Hebbian learning and is given by

$$\Delta w_{ji}(t) = \eta \left[y_j(t)x_i(t) - y_j(t)\sum_{k=1}^{j} w_{ki}(t)\, y_k(t) \right] \quad \ldots.(5)$$

Where $i = 1,2,\ldots,p$ and $j = 1,2,\ldots,l$ and $\Delta w_{ji}(t)$ is the change in the synaptic weight w_{ji}(t) at time t and η is the learning rate parameter.

Increment time t by 1, compute $y_j(t)$ and $w_{ji}(t)$ until weights reaches their steady-state values.

The GHA learns the first 'p' eigenvectors of covariance matrix in decreasing order of eigen values. GHA results in essential computations for saving memory if larger dimensions of input data are considered.

➢ ***Algorithm for image compression using GHA:***

Step 1: Initialize the weights to small random values at time t=1 and also assign a small positive value to learning rate parameter η.

Step 2: Load Image

Step 3: Calculate Principle Components for training image using equation 4 & 5.

Step 4: Increment time t by 1, go to step 3 until weights reaches their steady-state values.

Step 5: Normalization of the coefficients obtained in step 4.

Step 6: Obtain the Peak signal to noise ratio and display the reconstructed i.e. compressed image.

IV. EVALUATION PARAMETERS

The quality of the image can be measured using the parameters like Mean square Error (MSE), Peak signal to noise ratio (PSNR) and Compression Ratio (CR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The PSNR is an engineering term for the ratio between the maximum power of a signal and corrupting noise signal that affects the quality of the image. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression of the image. The signal is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR. A higher PSNR would normally indicate that the

Reconstruction is of higher quality.

- MSE is given by equation no. 6

$$MSE = \frac{1}{MN} * \sum_M \sum_N (I_1(m,n) - I_2(m,n))^2 \quad \ldots.(6)$$

Where M, N represent image size, $I_1(m,n)$ represents the original image and $I_2(m,n)$ represents reconstructed image.

- The PSNR is given by equation no. 7.

$$PSNR = 10log_{10}\left(\frac{L^2}{MSE}\right)(dB) \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(7)$$

Where L, is the maximum value in pixels of an image.

- The compression ratio (CR) is given by

$$CR = \frac{\text{size of original image}}{\text{size of compressed image}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

V. SIMULATION RESULTS

We applied Generalized Hebbian Algorithm to a standard single PNG grayscale image Lena of dimensions 512x512. The original image shown in figure 3 has a dimension of 512x512 and size of 148kB. Table 1 shows the compression results using GHA. For lesser value of compression ratio, PSNR(Peak Signal to Noise Ratio) value is large and the MSE value is less which gives a good quality reconstructed image for the mentioned method.

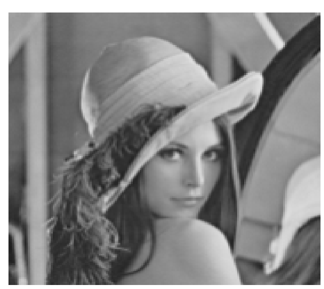

Fig. 3. Lena image (512x512 pixels) size 148kb.

The error calculated for this method is the error between the weights for the successive iterations. The GHA method leads to quick and iterative convergence to the principal components.

Table 1: Compression Results.

Sl.No	Compression Ratio	Error	PSNR (dB)
1	1.19	23.5	61.2
2	1.39	23.7	60.8
3	1.58	23.7	60.6
4	1.78	23.5	60.4
5	1.98	23.6	59.8

The reconstructed image shown in figure 4 is closer to original image having a compression ratio of 1.19 and PSNR of 61.2. The image is compressed to a size of 125kB.

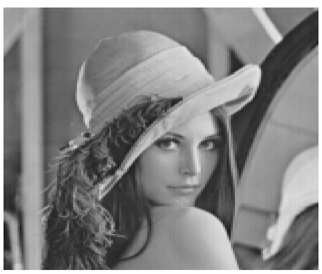

Fig. 3. Reconstructed image using GHA.

VI. CONCLUSIONS

This paper presents the applied generalized hebbian algorithm (GHA) to single grayscale image Lena of 512x512 pixels. The GHA method leads to quick and iterative convergence to the principal components. The results show that PSNR values are higher and hence a good quality reconstructed image is obtained.

The advantage of Generalized Hebbian Algorithm is that it does not require the storage space for covariance matrix. This is very useful when there is a larger dimensional covariance matrix.

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