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Computed Tomography Medical Image Compression using Conjugate Gradient

Saradha Rani S, Sasibhushana Rao G, Prabhakara Rao B

Abstract: ***Image compression which is a subset of data compression plays a crucial task in medical field. The medical images like CT, MRI, PET scan and X-Ray imagery which is a huge data, should be compressed to facilitate storage capacity without losing its details to diagnose the patient correctly. Now a days artificial neural network is being widely researched in the field of image processing. This paper examines the performance of a feed forward artificial neural network with learning algorithm as conjugate gradient. Various update parameters are considered in conjugate gradient methodology. This work performs a comparison between Conjugate gradient technique and Gradient Descent algorithm. MSE and PSNR are used as quality metrics. The investigation is carried on CT scan of lower abdomen medical image.***

Keywords**:** ***Neural Network, Compression, Gradient Descent, Conjugate Gradient, Performance Metrics***

I. INTRODUCTION

Because of the vast development in communication and multimedia technology, image storage is a key task in today's scenario. With the current major growth in e-health, telemedicine, teleconsultation and teleradiology, the interest of researching in the field of medical image compression is being increased [1]. In the medical field, storing a huge data in terms of Scan and X-Ray imaging is a challenge[2]. Therefore, compression is an important task in medical field. Medical images should be compressed in such a way that the subjective quality of the medical image is good so that the patient is diagnosed correctly i.e. the image is compressed while preserving its details. There are two methods of compressing an image , Lossless and lossy. Lossless compression technique recovers the original image accurately. Lossy compression technique removes psycho visual redundancies and attains higher compression ratios while degrading the image quality [3].The procedure of image compression can be illustrated in Fig. 1.

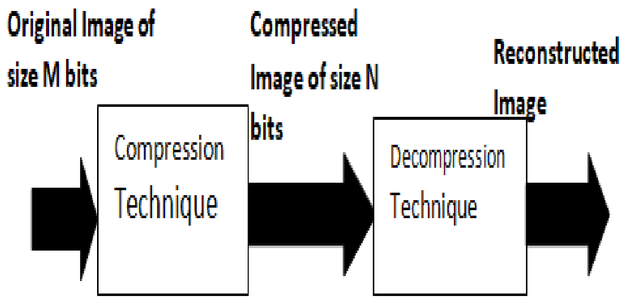

Fig.1. Diagrammatic representation of an image compression process

In this paper, Section II explains the basic structure of a neural network, Section III deals with the training algorithm, Section IV gives the performance metrics and in Section V results are discussed.

II. BASIC STRUCTURE OF A NEURAL NETWORK

Recently, implementing artificial neural network in the applications of image processing has been increased. Implementing NN for compressing the image comes under lossy compression method. Hence performance metrics are used to remark on method appropriateness [4].

An artificial neural network comprises of three layers namely input layer, hidden layer and an output layer [5]. The basic structure of a neural network is shown in Fig. 2. The NN is trained using Conjugate Gradient algorithm to compress an image. The number of neurons in hidden layer is comparatively less than the number of neurons in the input layer. The choice of number of hidden nodes depends on the compression ratio required. The unprocessed image is applied to the input node. The hidden layer output in concert with the weights related to the output nodes forms the compressed image [6,7].At the output layer, the decompressed image is obtained by multiplying the weights with the output at the hidden layer [8,9,10].

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***** Correspondence Author
S.Saradha Rani*, Dept.of ECE ,GITAM(deemed to be university),Visakhapatnam,Andhra Pradesh,India.
G.Sasibhushana Rao, Dept.of ECE, AU College of Engineering(A),AU,Visakhapatnam, Andhra Pradesh, India.
B.Prabhakara Rao, Dept.of ECE,JNT University, Kakinada, Andhra Pradesh,India.

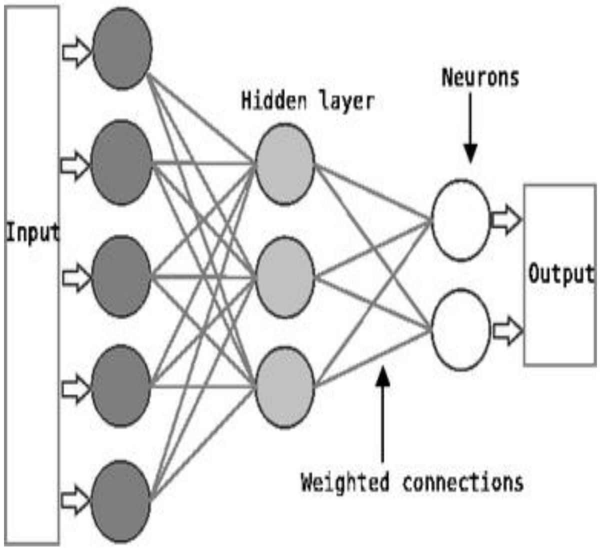


Fig.2.Basic structure of a Neural Network

III. CONJUGATE GRADIENT

In this paper gradient descent method is compared with conjugate gradient.

One of the well known and most popular iterative techniques is the conjugate gradient. The word conjugate stands for orthogonal, and hence orthogonal gradients[11,12]. The minimum of a function ,say Q(y), is obtained by setting the gradient equal to zero.

i.e., $$\nabla Q(y) = Ay - b = 0 \quad (1)$$

The solution is obtained by solving the residual

$$r = b - Ay \quad (2)$$

The sequence $\{y_k\}$ is such that the residual is orthogonal and is given by,

$$y_{k+1} = y_k + \alpha_k p_k \quad (3)$$

Where p_k is the search direction vector, α_k is a scalar that determines the step length.

The search direction is given by,

$$p_{k+1} = r_{k+1} + \beta_k p_k \quad (4)$$

The β which is the update parameter is of the various forms and is given as follows:

Fletcher-Reeves Update:

$$\beta_k = \frac{r_k^T r_k}{r_{k-1}^T r_{k-1}} \quad (5)$$

Polak- Ribiere Update:

$$\beta_k = \frac{\Delta r_{k-1}^T r_k}{r_{k-1}^T r_{k-1}} \quad (6)$$

Powell- Beale Restarts:

In conjugate gradient methods, the search direction resets from time to time to the negative gradient. Powell- Beale proposed a reset method that restarts if the orthogonality between the current and previous gradients is small. This is verified with following condition,

$$\left|g_{k-1}^T g_k\right| \geq 0.2\left\|g_k\right\|^2 \quad (7)$$

Conjugate gradient comprises of the following steps:

(i) For the first iteration, start searching in the direction of the steepest descent i.e. gradient negative.
(ii) Compute the steepest direction [13]
(iii) Calculate the update parameter by using any one of the above formulas.
(iv) Update the conjugate direction and position using the above formulas.
(v) Repeat steps (ii) to (iv) until maximum iterations reached.

IV. METHODOLOGY

The conjugate gradient algorithm and feed forward neural network is considered. Feed forward network is used for coding the image. First, an image is divided into sub-blocks and is scanned into a vector. All original image blocks is transmitted through the hidden layer consisting of H neurons with S synapses each, and is measured by chosen weight matrix. If H<S, such scheme produces image compression. The outputs of the hidden layer is passed through the output layer to obtain the decompressed image. Hence the hidden layer output is the compressed image and the output at the output layer is the decompressed image.

The network is trained using conjugate gradient with different update parameter.

A. Algorithm

a) Read the original image
b) Divide the image into blocks and scan into a vector.
c) Initialize the neurons
d) Apply the scanned vectors to each neuron in the input layer.
e) With the logic involved and the weights, accomplish the process and pass to the hidden layer.
f) Repeat the step in e)
g) Outputs obtained at hidden layer were applied to output layer with the corresponding weights to produce the decompressed image.

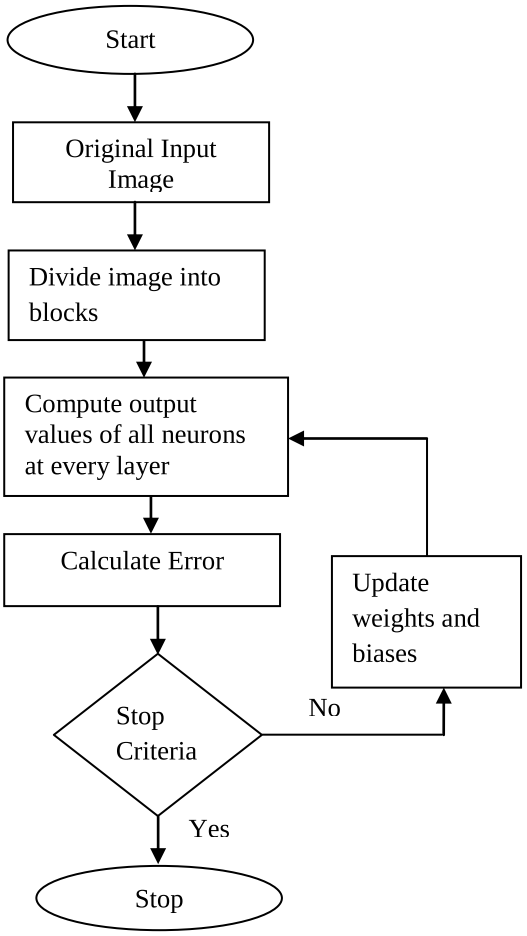


Fig.3.Flow chart describing the image compression

V. RESULTS AND DISCUSSION

The image quality is calculated using the metrics like Mean Square Error, MSE; Peak Signal to Noise ratio, PSNR and structural similarity index measure, SSIM. These define the reconstructed image quality at the output layer of ANN. The MSE should be possibly small i.e. the mean square error must be zero for ideal decompression.

$$MSE = \frac{1}{kl}\sum_{m=0}^{k-1}\sum_{n=0}^{l-1}[O(m,n) - R(m,n)]^2 \qquad (8)$$

$$PSNR = 20\ log\left(\frac{Max_i}{\sqrt{MSE}}\right)\ \text{dB} \qquad (9)$$

Where, O and R indicates the original and reconstructed images and Max_i represents the maximum of the pixel value.

Compression Ratio,

$$CR = \frac{uncompressed\ image\ size}{Compressed\ image\ size}$$
(10)

Table- I: Performance Comparison Of Gradient Descent And Conjugate Gradient

Training Function	For 8 Hidden Nodes		
	MSE	***PSNR***	***SSIM***
gd	5956.1	10.3812	0.0242
gdm	6.5859e+03	9.9446	0.0188
gda	721.4530	19.5487	0.2685
gdx	593.6624	20.3954	0.4308
cgb	65.5299	29.9664	0.8776
cgf	123.6758	27.208	0.7554
cgp	153.9872	26.256	0.7519
scg	88.7754	28.6479	0.836
oss	192.9324	25.2768	0.6884
rp	151.2115	26.335	0.7234

Table- II: Performance Comparison Of Gradient Descent And Conjugate Gradient

Training Function	For 16 Hidden Nodes		
	MSE	***PSNR***	***SSIM***
gd	7.49E+03	9.3885	0.0115
gdm	7.5393e+03	9.3575	0.0073
gda	887.7975	18.6477	0.2184
gdx	564.0124	20.6179	0.4145
cgb	30.3989	33.3022	0.9341
cgf	81.7935	29.0036	0.8351
cgp	48.3789	31.2842	0.8974
scg	59.1106	30.4141	0.8875
oss	124.9324	27.1641	0.7907
rp	130.7546	26.9662	0.7506

Table- III: Training time comparison of gradient descent and conjugate gradient

Training Function	Training time	
	8 Hidden nodes	*16 hidden nodes*
gd	3.5553	3.8442
gdm	5.0523	5.3681
gda	5.0136	5.3241
gdx	5.1552	5.5554
cgb	7.3392	7.9363
cgf	7.1734	7.9947
cgp	7.4185	7.9472
scg	3.6001	5.0807
oss	6.7914	7.43
rp	3.6001	3.7956

The performance of a neural network using conjugate gradient is carried on Computer Tomography medical image. The neural network is created with one hidden layer. The image is compressed with ‘8; and ‘16’ neurons in hidden layer. While, there are 64 neurons in the input and output layer.

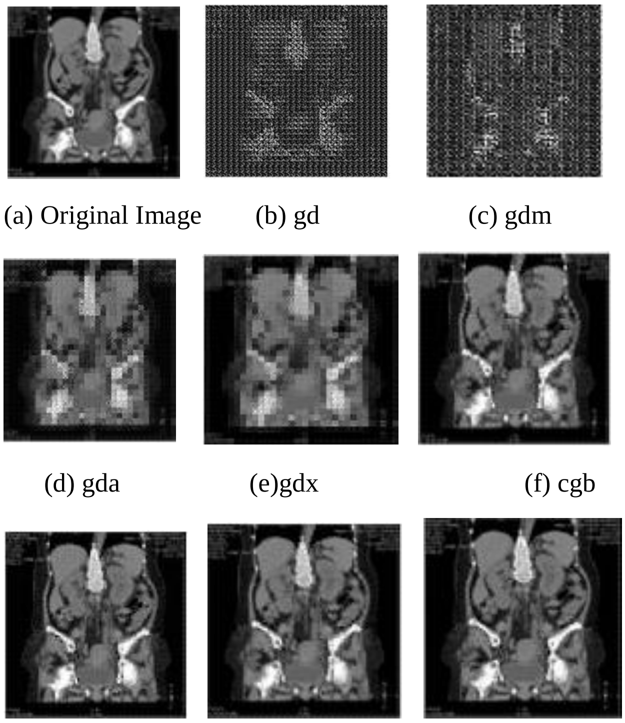
Experiment has been carried on CT image with different training algorithms to test the performance of a Feed forward neural network. The experiment is done for ‘1000’ epochs.

Table I compares the performance of gradient descent and conjugate gradient algorithms for ‘8’ hidden nodes in terms of MSE, PSNR and SSIM. Conjugate gradient with Powell-Beale restart performs better than gradient descent with values MSE as 65.5299, PSNR as 29.9664 and SSIM as 0.8776.

Table II compares the performance of gradient descent and conjugate gradient algorithms for ‘16’ hidden nodes in terms of MSE,PSNR and SSIM. Conjugate gradient with Powell-Beale restart performs better than gradient descent with values MSE as 30.3989, PSNR as 33.3022 and SSIM as 0.9341.

From Table I and Table II we can say that as number of hidden nodes increasing the quality of the image is also increasing. The compression ratio obtained for table I is 8:1 and for Table II is 4:1.

Table III illustrates the time required to train the network for ‘8’ and ‘16’ hidden nodes with different training functions. To train the network with conjugate gradient method requires more time than the time required to train the network with gradient descent algorithm for both ‘8’ and ‘16’ hidden nodes.

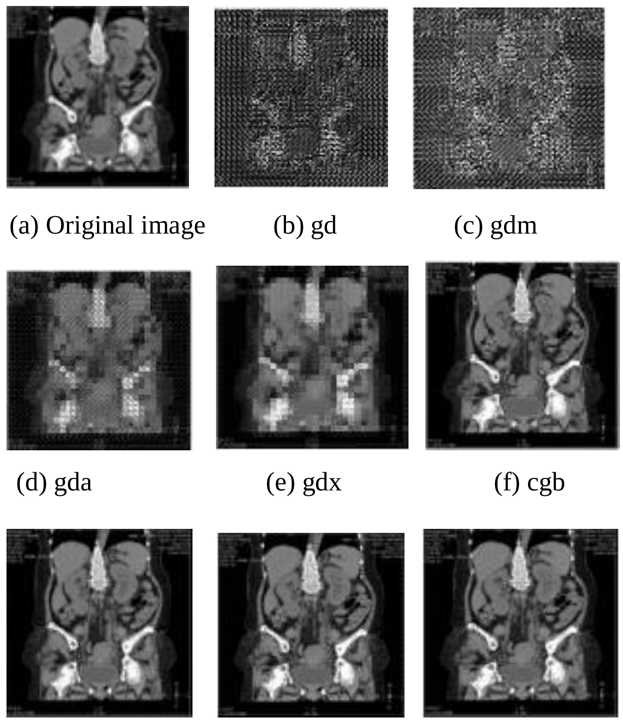


(a) Original Image (b) gd (c) gdm

(d) gda (e)gdx (f) cgb

(g) cgf (h) cgp (i) scg

Fig.4.Original and Reconstructed images a) – i) of CT scanned lower abdomen medical images with 8 hidden nodes, using gradient descent and conjugate gradient.



(a) Original image (b) gd (c) gdm

(d) gda (e) gdx (f) cgb

(g) cgf (h) cgp (i) scg

Fig.5. Original and Reconstructed images (a) – (i) of CT scanned lower abdomen medical images with 16 hidden nodes ,using gradient descent and conjugate gradient.

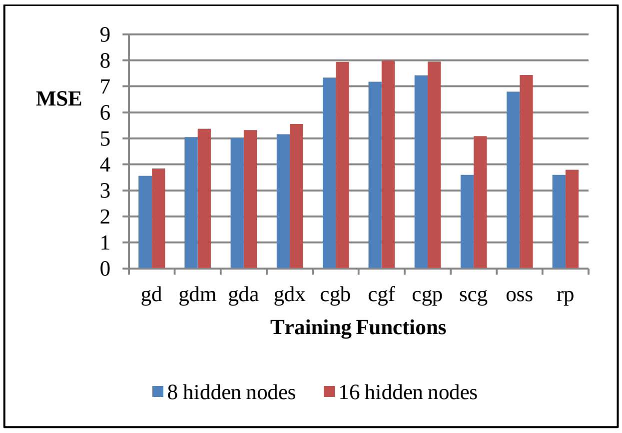


Fig.6. Graphs comparing MSE of various training functions for 8 and 16 hidden nodes

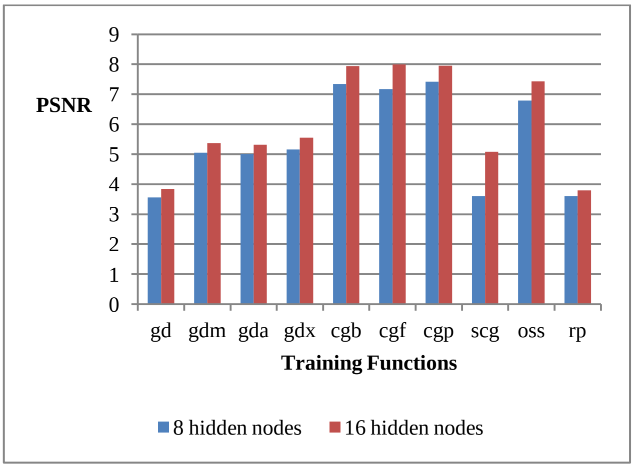


Fig.7. Graphs representing variation of PSNR with different training functions for 8 and 16 hidden nodes

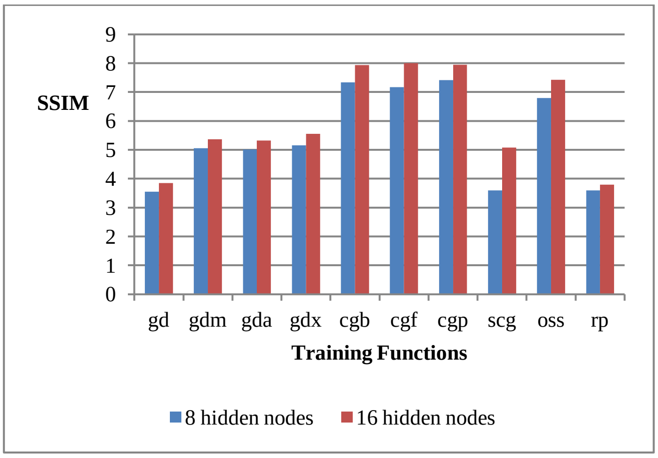


Fig.8. Graphs representing variation of SSIM with different training functions for 8 and 16 hidden nodes.

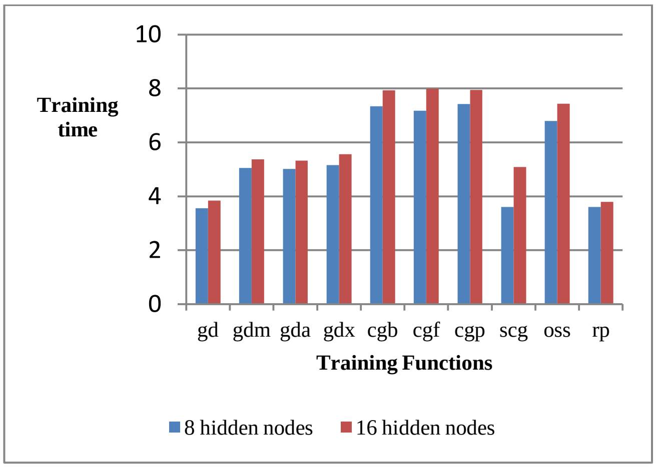


Fig.9. Graphs representing variation of Training time with different training functions for 8 and 16 hidden nodes.

Fig.4 and Fig.5 shows the original and reconstructed images of CT scanned lower abdomen medical image with 8 and 16 hidden neurons using gradient descent and conjugate gradient. From figures, it can be said that the subjective performance is good with conjugate gradient than gradient descent, that is, image is reconstructed with little distortion using CG than GD. Fig. 6 to Fig. 9 shows the variation of the quality measures like PSNR, MSE, SSIM and training time with various training algorithms for 8 and 16 hidden nodes.

VI. CONCLUSION

In this work, Conjugate gradient and gradient descent techniques that are based on artificial neural network is applied for compressing the CT scan of lower abdomen medical image. In conjugate gradient, the accurateness of the resultant outcome depends on the update parameter. The CG technique produces satisfactory results when compared to GD technique. The network is trained with 8x8 sub-blocks of image and tested for performance. A good image quality is obtained for CG, that is, it has high PSNR and SSIM, and low MSE. In image compression convergence time also play key task. The convergence of Conjugate gradient is earlier than gradient descent .The back propagation neural network with Conjugate gradient as learning algorithm improves the image compression and convergence time. Hence Conjugate gradient performs better both subjectively and objectively compared to gradient descent algorithm.

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AUTHORS PROFILE

S.Saradha Rani received B.Tech. in ECE from JNTU, Hyderabad, Andhra Pradesh in 2005 and M.Tech. in Radar & Microwave Engineering from Andhra University, Visakhapatnam, India in 2009 respectively. She is now working as Assistant Professor in GITAM(Deemed to be University), India. She is pursuing PhD degree in Image Processing at JNTUK, Kakinada. Her research interests include image and video processing and communications.

Prof.GottapuSasibhushana Rao is Professor in the Department of Electronics & Communication Engineering, Andhra University College of Engineering, Visakhapatnam, India. He is a senior member of IEEE, fellow of IETE, member of IEEE communication Society, Indian Geophysical Union (IGU) and International Global Navigation Satellite System (IGNSS), Australia. Prof. Rao was also the Indian member in the International Civil Aviation organization (ICAO), Canada working group for developing SARPS. He has published more than 485 Technical and research papers in different National / International conferences and Journals. His current research areas includes cellular and mobile communication, GPS, Bio medical and signal processing, under water image processing and optimization techniques.

B. Prabhakara Rao, received PhD from Indian Institute of Science, Bangalore, did his B.Tech. andM.Tech fromS.V.University. He is presently working as Programme Director, School of nanotechnology, JNTU, Kakinada, Andhra Pradesh, India. He has more than 35 years of teaching experience and more than 240 publications to his credit. His research interests include optical communications, wireless communications, microwave communications and image processing.