Chapter 4
Wavelet and Learning Based Image Compression Systems

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Abstract Image compression is a critical element in storage, retrieval and transmission applications. The list of traditional approaches to image compression has already been expanded by wavelet and learning based systems. Here, we report a few techniques which are based on discrete wavelet transform (DWT), Artificial Neural Network (ANN) in feedforward and unsupervised form. The experiments are repeated with images mixed with salt and pepper noise and the outcomes are compared. The quality of the image compression systems is determined by finding the mean square error (MSE), Peak Signal to Noise Ratio (PSNR) and Compression Ratio (CR).

Keywords ANN · MSE · CR · PSNR · SOM · DWT · DCT

4.1 Introduction

The use of data has increased significantly with the expansion of communication and multimedia applications. Uncompressed multimedia data require considerable storage capacity and transmission bandwidth [1]. Therefore, image compression is an essential requirement and has always been a growing area of research. The goal of image compression is to reduce memory requirements and bandwidth to transmit the image over a communication channel [2]. Image compression technique deals with reduction of redundancies present in an image. The situation is more critical with medical imaging. While for diagnostic applications, imagery volume is always increasing, the compression methods should never compromise the quality after decompression. Hence, there is a constant requirement to explore new methods of image compression which enhances quality. Learning based attributes in compression systems can provide better performance in this respect. Learning based

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tools like Artificial Neural Networks (ANN) have already received attention in this respect. Hence, the design of an efficient medical image compression system is a challenging task. ANNs have been applied to various image compression problems because of their ability to learn, retain the learning and use it subsequently which is not observed in traditional methods. They have the ability to preprocess input patterns to produce reduced data sizes with fewer components [3]. In such cases, ANN based systems don't require preprocessing blocks and reduce system complexity. Further, as ANNs are robust to noise variations, such systems show high level of resilience against sudden variations mostly essential for medical images. In order to perform image compression using ANNs, which is based on different learning algorithms, some topologies that have already been used are Multi-Layer Perceptron (MLP), Self-Organizing Maps (SOM), Learning Vector Quantization (LVQ) and Principal Component Analysis (PCA). The back-propagation learning algorithm used by MLP is a widely used method suitable for image processing applications. This feed-forward (FF) architecture of an ANN is capable of approximating most problems with high accuracy and generalization [4]. This ability of the FF ANN enables the user to use it for compressing images. Self-Organizing Feature Map (SOFM) is a kind of unsupervised ANN which consists of components called nodes (neurons) and is based on competitive learning. It gives a low dimensional and discretized representation of the input space of the training samples which is known as map [5]. The SOFM or SOM network is inherently a data clustering technique which can also be used for scaling data. The key point behind using SOM in image compression is its ability to make a proper approximation for a large set of data by detecting a smaller set of weights in the network. A large number of image compression techniques have been designed using conventional and ANN based methods. Some of the methods are spatial, time and frequency domain. But very few works are reported which have explored the possibility of deriving performance improvement by using the above techniques with learning based systems. Here, we present a comparative analysis between a learning aided image compression technique using MLP and another technique dependent on SOM and Discrete Wavelet Transform (DWT). The work describes a comparison between two lossy image compression schemes. The image to be compressed is decomposed into smaller sized blocks and then applied to either an MLP or a SOM network followed by DWT for compression. The compressed image is reconstructed using an MLP in the first approach. In the second method, the image after compression is recovered by a composite block formed using a FF ANN and a Discrete Cosine Transform (DCT) based compression-decompression system. The original image is degraded to some extent by adding salt and pepper noise to it in order to check whether the image compression systems are robust to degradations like noise. The performance of the systems is evaluated by determining the Mean Square Error (MSE), Compression Ratio (CR) and Peak Signal-to-Noise Ratio (PSNR). The remaining part of the paper is divided into the following sections. Sections 4.2 and 4.3 describes literature review and background theory. The presented system models and comparison analysis is explained in Sects. 4.3 and 4.4. Conclusion part of the proposed work is discussed in Sect. 4.5.

4.2 Literature Review

1. In [3], the authors proposed a method on improved image compression approach with SOFM Network using Cumulative Distribution Function. This work provided improved CR and network convergence.
2. In [4], digital image compression using neural networks has been reported. The ANN algorithm used here is mainly the back-propagation of multilayer perceptrons. The algorithm preserves most of the characteristics of the image and maintains the compression performance.
3. In the work [5], the authors proposed a work on image compression technique based on DWT and Self Organizing Map. In this work, a better CR and PSNR is attained compared to existing techniques.

4.3 Certain Theoretical Concepts

Here, we discuss the related theoretical concepts.

4.3.1 ANN in FF Mode

An ANN is a highly interconnected network of a large number of processing elements called neurons in an architecture inspired by the brain [6, 7]. The network consists of three layers, the input layer, the hidden layer and the output layer which are interconnected to each other layers as shown in Fig. 4.1. The network can be trained with input patterns to achieve the desired output.

4.3.2 SOM

SOM network is a kind of unsupervised ANN based on competitive learning algorithm. Here, the output neurons compete with each other to get activated. The architecture of SOM network is shown in Fig. 4.2. The SOFM algorithm is based on two basic expressions shown in (4.1) and (4.2). For a network with n number of neurons and at time t, if x is the input then

$$\|x(t) - w_c(t)\| = min\|x(t) - w_i(t)\| \tag{4.1}$$

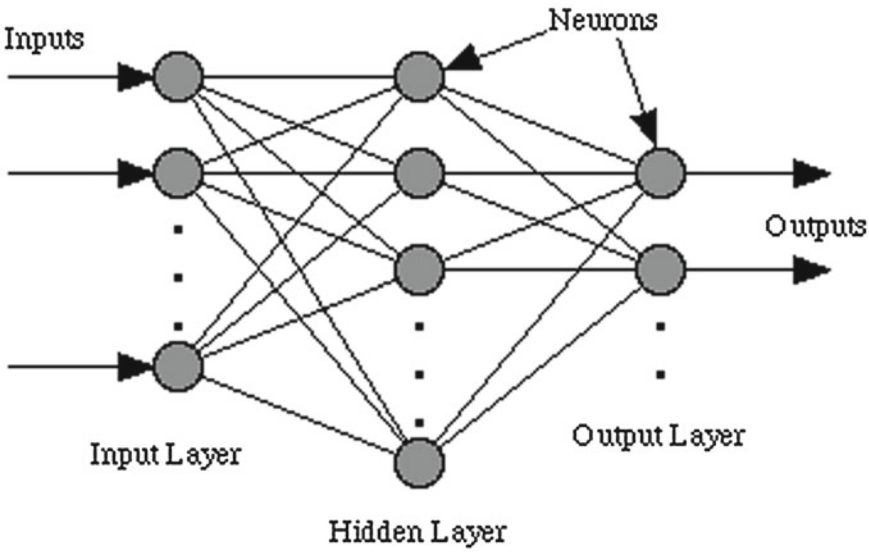

Fig. 4.1 Structure of an ANN

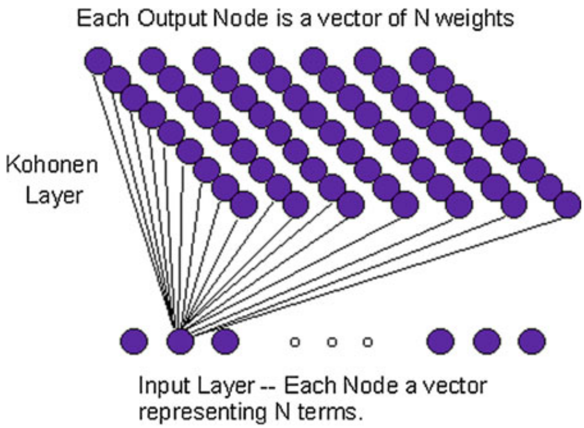

Fig. 4.2 Architecture of SOFM network

$$w_i(t+1) = w_i(t) + \alpha(t)[x_i(t) - w_i(t)] \tag{4.2}$$

where, $1 < i < n$, w_i is the node, w_c is the winner and α is the learning rate, $0 < \alpha < 1$.

4.3.3 DWT

DWT decomposes the input data into a set of wavelets, orthogonal to its translations and scaling. When we apply single level DWT to the input data, four sub-bands, LL, LH, HL and HH are formed as shown in Fig. 4.3. Only the LL sub-band containing useful information regarding the image quality is considered and processed for reconstruction. In the proposed work, single level decomposition using Haar DWT is performed.

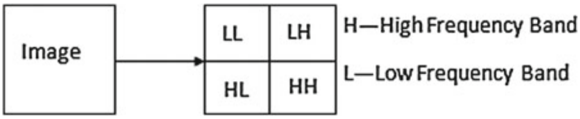

Fig. 4.3 Decomposition using DWT

4.3.4 DCT

DCT is one of the most popular compression scheme for still image compression. The property of energy compaction found in DCT and availability of fast algorithms applicable for real operations makes it suitable for use in image compression. DCT helps in separating an image into spectral sub-bands of differing importance with respect to image's visual quality [8]. For an image block of size 4×4, the ordering in frequency is shown in Fig. 4.4. The lower frequencies are denoted by smaller numbers.

0	1	5	6
2	4	7	12
3	8	11	13
9	10	14	15

Fig. 4.4 Zigzag scan of DCT coefficients

4.4 Image Compression Models

The proposed learning based image compression systems have certain constituent block which are discussed in the following sections.

4.4.1 Image Compression System Using FF ANN

The ANN used for compression in the proposed method is of the type MLP trained with back-propagation algorithm. The parameters of the ANN is shown in Table 4.1. A sample image of size 256 × 256 is considered initially. The system model is shown in Fig. 4.5. The image is sent to two ANNs for compression and decompression. The quality of the reconstructed image is found to be poor when the whole image is given as input to ANN. In order to improve the quality of the reconstructed image, multi-level decomposition of the image is done. Decomposition of an image into sub-blocks reduces computational complexity of the system [9]. We describe a 4-level and 9-level decomposition done to perform image compression using ANN. Different patterns are presented to the ANN which it learns during training. The learning is preserved and used subsequently. In 4-level decomposition, the image to

Table 4.1 ANN parameters

ANN type	Training algorithm	Training function	Epochs	MSE goal
Feed–forward MLP with 2 *hidden layers*	Backpropagation *Levenberg–Marquardt* Optimization	*Trainlm*	1–100	10^{-6}

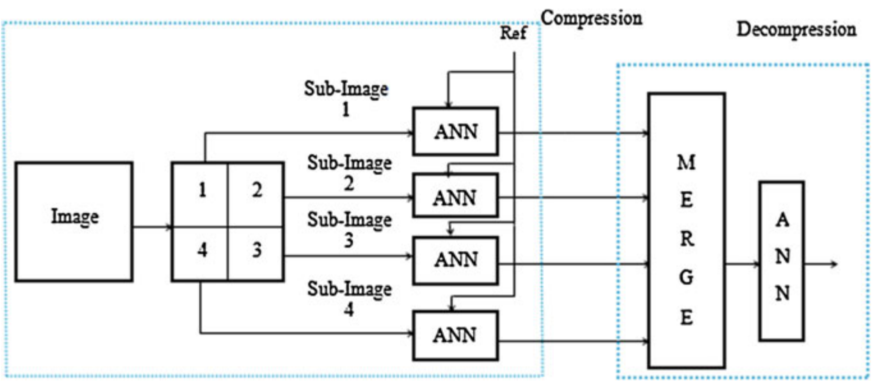

Fig. 4.5 Block diagram of compression system using ANN

Table 4.2 Simulation parameters

Item	Description
Data dimension	128×128
	256×256
	512×512
Data size	10 *samples each of the above dimensions both in noise free and noise mixed form*
Tools	*ANN in FF form, SOM, DWT and DCT*

be compressed is partitioned into four equal sized blocks. Each block is then sent to an ANN for compression, by selecting a suitable reference. The compressed sub-images are combined to achieve a CR of 128:1 for an original image of size 256×256. Although, the compression rate achieved in this compression system is high, yet the image quality after reconstruction is not up to the level of an acceptable limit. Hence, higher level decomposition is done and it is seen that 9-level decomposition gives better results. The simulation parameters are given in Table 4.2.

4.4.2 *Image Compression Based on SOM and DWT and Reconstruction Using FF ANN*

The decomposed parts of the original image of size $m \times n$ are sent to a SOM network individually for generating the weight matrices, also known as the codebook. The size of the codebook generated by SOM is kept fixed at $64 \times n/2$. There will be four weight matrices or codebooks with respect to each sub-image. The weight matrix is decomposed into four sub-bands by applying single-level DWT to it. The four components formed after single-level decomposition are the approximation coefficient (LL), the horizontal coefficient (LH), the vertical coefficient (HL) and the diagonal coefficient (HH). Among the four components, only the LL part contains useful information required for preserving the image quality. The other coefficients (LH, HL and HH) contain very less information details and if they are discarded, the quality of the reconstructed image is not hampered. The LL part is retained to get the compressed sub-image. For each sub-image, the above compression procedure is repeated which gives a compressed image of size $64 \times n/2$ with a CR of 8:1. The block diagram of the just described compression system is shown in Fig. 4.6. The decompression process uses an ANN in multi-layer feed-forward form containing a single hidden layer. The compressed sub-image is fed as input to the ANN along with a reference. The reconstructed matrix generated on application of DCT based compression and decompression to the original image sub-blocks is taken as the reference. The decompression scheme for the regeneration process is shown in Fig. 4.7. The ANN parameters are shown in Table 4.3. The size of layers will vary with respect to four and nine level decompositions.

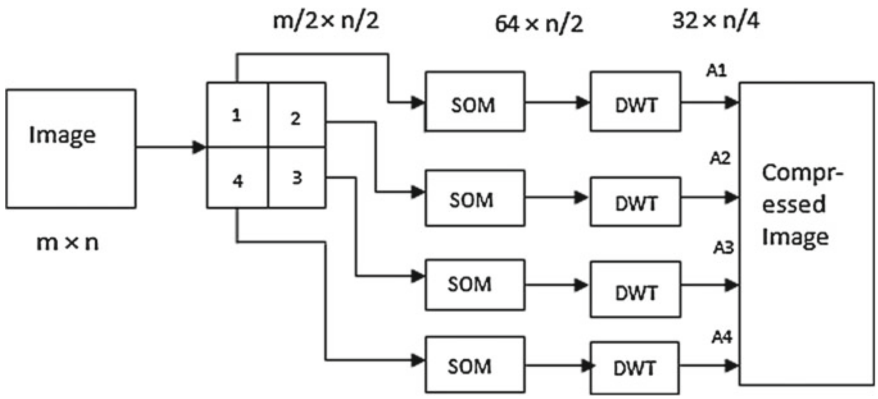

Fig. 4.6 Block diagram of compression system using SOM and DWT

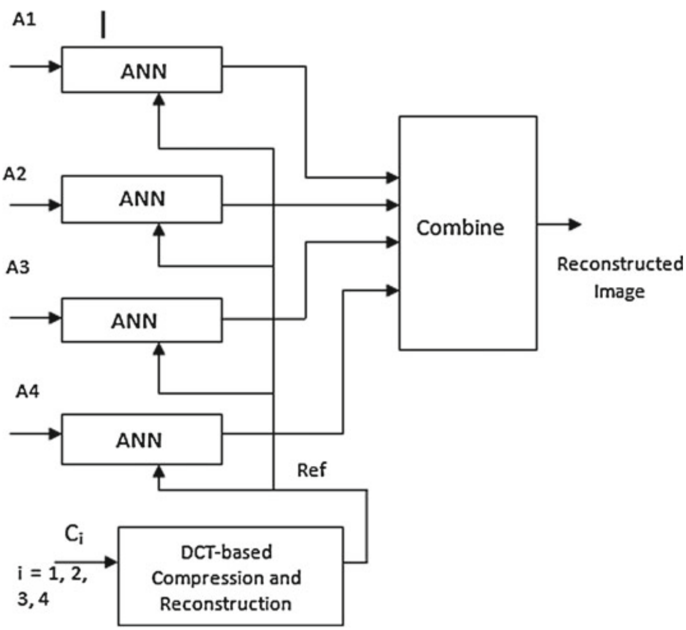

Fig. 4.7 Block diagram of decompression scheme

Table 4.3 ANN Parameters

Network topology	SOM grid, one layer	MLP, one input, one hidden, one combined output
Size		$32 \times n/4$
	$64 \times n/2$	$1.5 \times$ input layer size
		$64 \times n/2$
Training type	*Competitive* learning	Back-propagation with *Levenberg–Marquardt* optimization
Epochs	100–500	50–200
MSE goal	–	10^{-3}

4.5 Comparative Analysis

The performance of the two image compression systems are evaluated by finding parameters like MSE, CR and PSNR. The computational time required for the two systems are also calculated. Table 4.4 shows the experimental results for three different sample images of MRI, CT scan and X-ray. In the table, system 1 refers to image compression technique using FF ANN whereas system 2 represents image compression system using SOM and DWT. The two systems are analyzed based on these results. From Table 4.4, it is seen that the proposed image compression schemes differ from each other in terms of CR, PSNR and computational time. System 2 undergoes image compression without requirement of a reference unlike system 1. The image quality after reconstruction is maintained in both the cases which is judged by finding out the MSE. The system is experimented for various medical images and the performance is found out to be satisfactory. The experimental results for a sample image of X-ray is shown in Fig. 4.8. The recovery of the original image for the two proposed systems is satisfactory which can be viewed from Fig. 4.8. This enables the users to use the system for storage and transmission purposes with medical images. The PSNR values that are evaluated experimentally, shows the robustness of the systems. The compressed images can be transmitted through communication channels irrespective of degradations like noise that may be present in an image due to false switching of a device and transmission media. Thus with the FF form described in Sect. 4.1, the CR is found to be high but computational requirement are found to be more and decompression quality is lower making it unsuitable for medical applications. Next, the SOM-DWT-FF ANN combination provides lower compression but has superior decompression quality, shows less computational requirements and is also robust against noise like variations. Thus, this approach is suitable for medical applications even when images are transmitted using certain communication systems. The method when compared with Run-length Encoding (RLE) also provides better quality but is computationally demanding. Tables 4.5 and 4.6 shows the comparison of MSE and PSNR values of the proposed systems with existing RLE.

Table 4.4 Performance evaluation

Image	Original size	CR for system 1	CR for system 2	MSE, system 1	MSE, system 2	PSNR, system 1	PSNR, system 2	Computational time, system 1 (s)	Computational time, system 2 (s)
MRI	240 × 240	80:1	15:2	0.015	0.007	65.52	69.41	3465.15	153.00
CT scan	240 × 240	80:1	15:2	0.018	0.010	64.97	67.30	2877.50	138.20
X-ray	240 × 240	80:1	15:2	0.040	0.007	65.57	69.60	3251.44	133.37

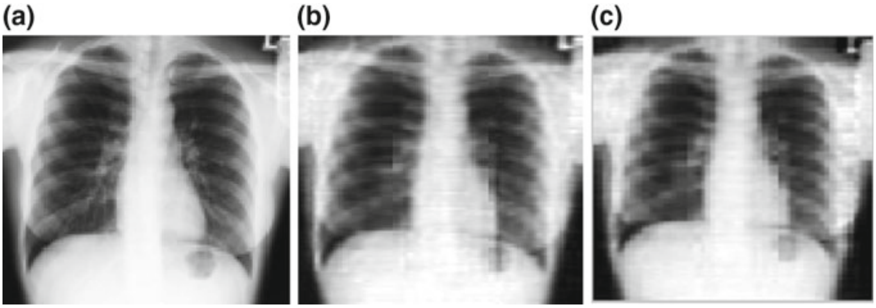

Fig. 4.8 Original and reconstructed images for the proposed systems. **a** Original image. **b** Reconstruction (system 1). **c** Reconstruction (system 2)

Table 4.5 MSE comparison of proposed systems with existing RLE

Image	MSE, RLE	MSE, system 1	MSE, system 2
MRI	0.36	0.015	0.007
CT Scan	0.34	0.018	0.010
X-ray	0.32	0.040	0.007

Table 4.6 PSNR comparison of proposed systems with existing RLE

Image	PSNR, RLE (dB)	PSNR, system 1 (dB)	PSNR, system 2 (dB)
MRI	52.56	65.52	69.41
CT Scan	52.79	64.97	67.30
X-ray	52.98	65.57	69.60

4.6 Conclusion

Here, we discussed certain approaches for image compression with the objective of making it suitable for medical applications. We proposed a FF ANN and a SOM-DWT-FF ANN based approaches out of which the later is found to be more suitable.

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