Chapter 1
Data Security in the Cloud via Artificial Intelligence with Vector Quantization for Image Compression

Srinivasa Kiran Gottapu and Pranav Vallabhaneni

1.1 Introduction

Images play a vital role in today's digital world; they are used as a representation object. They are widely used in gaming, television, satellites, mobile phones and medical field. Images are the latest internet sensations where they are used to showcase about a person in social media websites. When an image is captured, a huge amount of data is also produced which makes it infeasible for storage as well as transmission. A solution for such problem is image compression, where the original data is reduced by fewer bits without compromising on the image quality, by removing the redundant information and restoring the useful and important information.

There are basically two types of compression techniques:

1. Lossless
2. Lossy

Lossless compression technique is a form in which compression takes place without loss of any data or without any quality loss. It is an exact copy of the original image. Such type of compression has applications in the field of medicine where loss of any data can result in an improper and poor diagnosis, in business documents, text documents, source code, etc.

On the contrary, lossy compression technique is a form in which compression takes place with loss of some redundant and unwanted data, where some com-

S. K. Gottapu (✉)
Department of Electrical Engineering, University of North Texas, Denton, TX, USA

P. Vallabhaneni
Department of Computer Science and Engineering, Sir C. R. Reddy College of Engineering, Eluru, India

A. Haldorai et al. (eds.), *EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing*, EAI/Springer Innovations in Communication and Computing, https://doi.org/10.1007/978-3-030-19562-5_1

promise on quality is acceptable. Such compression techniques are used where the requirement of compression is high and where some loss of information is acceptable. They are usually used for storage purposes or for transmission through web.

Objective: The main objective of this chapter is to introduce an algorithm which combines an artificial intelligence technique with a standard compression technique to achieve desirable compression ratios. The flow of the chapter is as follows: Sect. 1.1 gives an overall introduction about the image compression. Section 1.2 is about the related work done in image compression, a survey on related standard papers and their methodologies and results are discussed. Section 1.3 gives a detailed explanation of the proposed algorithm with flow charts and stepwise explanations. Section 1.4 includes the results and observations obtained through the proposed algorithm. Section 1.5 concludes the report with scope for the future work using this algorithm.

1.2 Literature Survey

In [1] a single hidden layer neural network with four neurons in the hidden layer is used for image compression. A vector quantizer with codebook of 256 code vectors is used in the hidden layer for digital transmission of 0.5 bpp. In an input that is a sub-image of size 4×4 pixels, 16 pixels is given as input to the network. The output vector from the hidden layer is smaller than the size of the input vector because the input contains 16 neurons whereas the hidden layer consists of only 4 neurons which gives the compressed form of the data. The sub-image is reconstructed at output layer which consists of 16 neurons like the input layer. The analysis of results is carried out by comparing the proposed technique with various other compression techniques that include VQ as residual technique in it. The proposed technique is also compared with 8, 12, 16 hidden neural network. The results show that a good level of PSNR of about 30 dB is obtained with the proposed technique with different number of neurons in hidden layer than the other compression techniques used in comparison.

In [2], the work is on 2-Dimensional Discrete Wavelet Transform (2D-DWT) with Multistage Vector Quantization (MSVQ). The code-book is generated using LBG algorithm for vector quantization (VQ) in different stages. The Radial Basis Function (RBF) neural network is used for training the indices in the MSVQ stages. The method is then applied for different techniques for comparison such as the DCT and (2D-DCT). This method is applied on multiple images of resolution 128×128 each. The applied method gives better results in terms of image quality like the PSNR and compression ratio as compared to other transforms. The evaluation of proposed scheme is based on the compression efficiency and distortion measures. The result shows that the output obtained from the above method generates a high-quality compressed image along with better PSNR value and low MSE.

In [3] two levels of VQ are applied. One is applied on the transformed image obtained by hybrid wavelet transform and then it is applied on the error image. At both the levels of VQ generation same size of codebook is obtained. At the first the original image is compressed using transform and an acceptable compression ratio of about 42.6 is obtained, but it produces some distortion. So therefore the VQ is then applied on transformed image for better compression and quality of the image. The combination of these two techniques increases the compression ratio. The obtained distortion in transform technique is eliminated by applying VQ on the error image and then both these compressed images are added which reduces the distortion by 10%.

In [4] compression technique is proposed for gray scale medical images using feed forward neural network along with the back propagation algorithm. The MRI image is applied on the network that consists of three hidden layers. Training is first performed on sufficient sample images to store the node weight and activation values and then it is applied on the targeted image. A compression is achieved since hidden neurons are less in number than the input image pixels. The algorithms are tested for different number of compressor nodes and for different sub-image block size and the performance is evaluated for the compression ratio and PSNR. The algorithm has compression ratio of 1:30 to JPEG2000 with PSNR of 39.56 dB. Therefore the chapter concludes that FNN can achieve good compression performance to the existing techniques for medical images.

1.3 Methodology

The methodology mainly consists of the five steps included in the flowchart as shown in Fig. 1.1.

Input Image: here an image is read from the files which acts as the original image in the process. This image is fed as an input to the next step and on which the compression takes place. The input image can be of any format such as jpg, png, and tiff. The file size of the input image is calculated so as to compare it with the final compressed image [5].

Image pre-processing: image pre-processing is performed on the input image; it performs some necessary and application-specific changes in the input image that makes it ready for the next step of compression. The image pre-processing consists of the steps shown in Fig. 1.2.

Vector Quantization: A lossy data compression technique is a widely used technology for data storage and transfer. VQ makes use of the rounding off technique or it optimally approximates from an input data to an output data. The compression in VQ is obtained using the 'Codebook', which contains the approximated [6] values using some sort of clustering technique like K-mean clustering. The codebook is used to map the original data or input data to some approximated values which gives the compressed output [7].

Fig. 1.1 Flowchart for Image compression

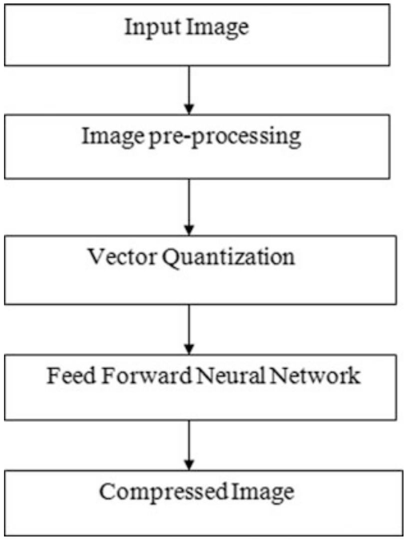
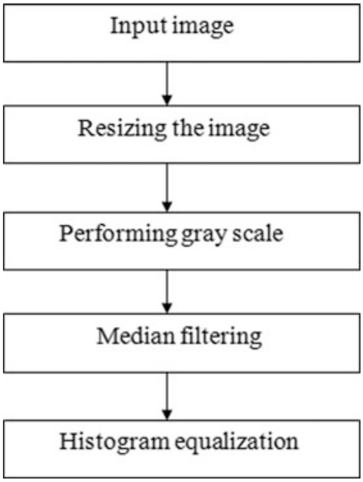


Fig. 1.2 Image pre-processing flowchart



1.4 Results

The compression is performed on the standard Lena image as shown in the picture above. The input image is of the resolution of 512 $\times$ 512 pixel and is of the size 32,637 bytes. The compression is performed for different values of K (number of centroids). The range of K depends upon the input image resolution and the tile size. The tile size chosen here is 8; therefore each tile will contain 8 $\times$ 8 = 64 pixels, and the input image resolution is 512 $\times$ 512 = 262,144 pixels. No. of tiles = 262,144/64= 4096 tiles. Therefore the value of K can range from 0 to 4096, for

Table 1.1 Compression parameters

	Compression ratio	SNR	PSNR
$K = 50$	2.09	13.67	19.32
$K = 100$	1.95	13.76	19.42
$K = 150$	1.85	13.81	19.47
$K = 200$	1.80	13.85	19.50
$K = 250$	1.70	13.9	19.60
$K = 500$	1.70	13.95	19.61
$K = 1000$	1.63	13.9	19.60

Table 1.2 Compressed file sizes

	Original image size (in kb)	VQ image size (in kb)	Final image size (in kb)
$K = 50$	32.637	16.722	15.598
$K = 100$	32.637	18.243	16.661
$K = 150$	32.637	19.701	17.566
$K = 200$	32.637	20.150	17.852
$K = 250$	32.637	21.103	18.534
$K = 500$	32.637	23.492	19.148
$K = 1000$	32.637	25.415	19.975

512×512 input image and tile size 8. But we prefer to study the observations for the ideal values of K that range between 50 and 250, since greyscale image has colour intensities between 0 and 255. But additionally we can even compare it with higher values than 255. Therefore the values K chosen are 50, 100, 150, 200, 250, 500 and 1000.

Tables 1.1 and 1.2 give the compression parameters. We observe that as the value of K increases from 50 to 1000 the compression ratio decreases and the PSNR increases. We observe that a compression of about half the size of the original image is obtained with an average PSNR of 20 dB.

1.5 Conclusion

Images are an important part of the digital world today. They are used as representation objects in various fields like medicine, satellites, televisions, and internet. So therefore storing and transmitting of these images needs an efficient solution to reduce their cost of storage and transmission. Hence we make use of the various compression techniques. In this project, a compression algorithm using both Vector Quantization (VQ) and Feed Forward Neural Network (FFNN) is introduced. On the input image (standard image Lena) the VQ is applied first using the K-Mean Clustering with a tile size of 8, and some compression is achieved. The VQ compressed image acts as an input to FFNN and an additional compression is achieved. The results and observations indicate that an acceptable amount of compression ratio of around 2 which is half of the size of the original image and PSNR of about 20 dB is achieved. It is observed that as the value of K (number of centroids) increases from 50 to 1000 for the set of observations, it is seen that the compression ratio decreases and PSNR increases.

References

1. E.M. Saad, A.A. Abdelwahab, M.A. Deyab, Using feed forward multilayer neural network and vector quantization as an image data compression technique, in *Proceedings of the Third IEEE Symposium on Computers and Communications, 1998, ISCC'98*, Athens, 1998, pp. 554–558. https://doi.org/10.1109/ISCC.1998.702592
2. V.D. Raut, S. Dholay, Analyzing image compression with efficient transforms & multistage vector quantization using radial basis function neural network, in *2015 IEEE International Conference on Engineering and Technology (ICETECH)*, Coimbatore, 2015, pp. 1–6. https://doi.org/10.1109/ICETECH.2015.7275009
3. P. Natu, S. Natu, T. Sarode, Hybrid image compression using VQ on error image, in *2017 International Conference on Intelligent Communication and Computational Techniques (ICCT)*, Jaipur, 2017, pp. 173–176. https://doi.org/10.1109/INTELCCT.2017.8324040
4. W.K. Yeo et al., Grayscale medical image compression using feedforward neural networks, in *2011 IEEE International Conference on Computer Applications and Industrial Electronics (ICCAIE)*, Penang, 2011, pp. 633–638. https://doi.org/10.1109/ICCAIE.2011.6162211
5. P.K. Shah, R.P. Pandey, R. Kumar, Vector quantization with codebook and index compression, in *2016 International Conference System Modeling & Advancement in Research Trends (SMART)*, Moradabad, 2016, pp. 49–52. https://doi.org/10.1109/SYSMART.2016.7894488
6. W. Zhang, H. Li, X. Long, An improved classified vector quantization for medical image, in *2015 IEEE Tenth Conference on Industrial Electronics and Applications (ICIEA)*, Auckland, 2015, pp. 238–241. https://doi.org/10.1109/ICIEA.2015.7334118
7. A.J. Hussain, A. Al-Fayadh, N. Radi, Image compression techniques: a survey in lossless and lossy algorithms. Neurocomputing **300**, 44–69 (2018)