IMPROVEMENTS ON GENERALIZED RESIDUAL VECTOR QUANTIZATION BASED IMAGE COMPRESSION

[1]Divya A and [2]Dr.Sukumaran S
[1]Ph.D Research Scholar, Department of Computer Science, Erode Arts and Science College, Erode, Tamil Nadu, India
[2]Associate Professor, Department of Computer Science, Erode Arts and Science College, Erode, Tamil Nadu, India

Abstract : Vector quantization (VQ) is the powerful technique in the field of image compression. The aim of image compression is reduced the bit rate for transmission or data storage at the same time maintaining an acceptable fidelity or image quality. However, VQ is provided less efficiency in a high dimensional data. The performance of VQ was enhanced through presenting the generalized residual vector quantization which was optimized by Particle Swarm optimization (PSO) and Honey Bee Mating Optimization (HBMO) algorithms. Furthermore, the artificial plant optimization algorithm was optimized the parameter of Generalized Residual Vector Quantization (APOA-GRVQ) for maintaining the images quality. The APOA-GRVQ was suffered due to time complexity issue. This issue was handled by presenting Adaptive Optimized image compression (AOIC) method which was adaptively selected the VQ and GRVQ for reducing the codebook generating time. In this paper enhanced the performance of generalized residual vector quantization (EGRVQ) for generating the optimal codebook. The EGRVQ is performed generalized vector quantization with higher accuracy. The EGRVQ is performed in to three phases namely transition clustering, multipath encoding and ∈-term elimination. In a transition clustering phase, the k-means algorithm is presented in conventional GRVQ which was suffered convergence to local minimum. So, the Non-negative Matrix Factorization (NMF) clustering algorithm is presented in proposed EGRVQ to optimally reduce the size of codebook. In multipath encoding phase, reduce the computation error of codebook. For elimination of ∈-term, the Euclidean distance computation was performed in conventional GRVQ which was suffered by computational complexity. So, the mahalanobis distance Computation is presented to eliminate ∈-term in proposed EGRVQ for achieving optimal quantization accuracy. The performance of proposed method is evaluated in terms of Compression Ratio, Peak-Signal Noise Ratio (PSNR), Structural Similarity, and Bit Rate.

***IndexTerms* - Codebook, VQ, PSO, HBMO, GRVQ, APOA and encoding.**

I. INTRODUCTION

The image compression technique [9] can be used in the areas of high information volume for reducing the bit rate in an image. VQ is a relatively efficient coding technique in digital image compression area. One important feature of VQ is the possibility of achieving high compression ratios with relatively small block sizes. Another features of VQ image compression its fast decompression by table lookup technique. VQ is provided less efficiency in a high dimensional data. The generalized residual vector quantization (GRVQ) is optimized by Particle Swarm optimization (PSO) and Honey Bee Mating Optimization (HBMO) algorithm [2] to further improve the performance of the vector quantization methods. The GRVQ (Liu, S., et.al.2016) is to iteratively select a codebook and optimize it with the current residual vectors, then re-quantize to obtain the new residual vectors for the next iteration.

Moreover, the artificial plant optimization algorithm was optimized the parameter of Generalized Residual Vector Quantization (APOA-GRVQ) for maintaining the images quality. The APOA-GRVQ was suffered due to time complexity issue. The Adaptive Optimized image compression (AOIC) method was handled this issue efficiently which was adaptively selected the VQ and GRVQ for reducing the codebook generating time. In this paper enhanced the performance of generalized residual vector quantization (EGRVQ) for generating the optimal codebook. The EGRVQ is performed generalized vector quantization with higher accuracy. The EGRVQ is performed in to three phases which are transition clustering, multipath encoding and ∈-term elimination. The effectiveness of the proposed approach is tested with Compression Ratio, Peak-Signal Noise Ratio (PSNR), Structural Similarity, and Bit Rate.

II. LITERATURE SURVEY

An effective algorithm [6] was presented to generate codebook which was used the sorting method to generate codebook and the code vectors were obtained by using median approach. The proposed algorithm was compared with kekre's proportionate error algorithm (KPE) in terms of mean squared error (MSE), PSNR and codebook generation time. The result shows the proposed algorithm was provided better performance than conventional LBG algorithm.

The evolutional particle swarm optimization (PSO) learning scheme [3] was proposed to determine optimal parameter of the fuzzy inference system (FIS) which were generated appropriate codebooks with the decision of the soft fuzzy inference analysis for achieving the application of image compression. The proposed approach was utilized the adaptive learning scheme of the PSO and the flexible membership function of the fuzzy inference system to achieve the optimal outcome. Moreover, this approach were solved the local minimal problem of the traditional LBG algorithm.

The multipath tree structure vector quantization (TSVQ) algorithm [1] was proposed to improve the quality of an image by increasing the number of search paths traversed to find the closest codeword. The novel full search equivalent TSVQ (FSE-TSVQ) was obtained efficiently the closest codeword for each input vector. FSE-TSVQ was performed the triangle inequality to achieve efficient pruning of impossible codewords. Furthermore, this research was developed the enhanced DP-TSVQ algorithm for achieving a better trade off than DP-TSVQ encoding time and image quality. EDP-TSVQ was a hybrid technique which added DP-TSVQ's critical function to FSE-TSVQ. EDP-TSVQ provided an image quality identical to that of DP-TSVQ, but by searching fewer codebook tree nodes. The experimental result shows, the performance of EDP-TSVQ was provided better performance than FSE-TSVQ, DP-TSVQ and conventional TSVQ techniques.

An entropy-constraint reflected residual VQ (EC-RRVQ) [10] was proposed for performing large block vector quantization. The reflected residual VQ, a type of multistage VQ, had constraint structure with multiple stages had been small size code books. The utilization of multiple code-books and reflection constraints makes the computational complexity linearly depend on the number of stages involved. The EC-RRVQ was reduced inter stage dependencies at large vector dimensions, which had an effective design to realize large-dimensional vector quantization systems.

The novel method based on firefly algorithm [5] was proposed for constructing the codebook of vector quantization. The proposed method was utilized the LBG method as the initial of firefly algorithm to implement the VQ algorithm. The method was referred as FF-LBG algorithm. The computation of the proposed algorithm was faster than the PSO-LBG and HBMO-LBG algorithms. The proposed FF-LBG algorithm was provided the better codebook with smallest distortion and the least computation time than the LBG, PSO-LBG and HBMO-LBG algorithm.

An effective and efficient method [12] was presented for increasing the speed of the ant colony optimization (ACO) for solving the codebook generation problem (CGP). The result shows the proposed approach was significantly reduce the computation time of ACO-based algorithms. The proposed algorithm was efficiently detect and compress patterns that were essentially redundant during the evolution process of ACS for CGP so that most of the computations applied to these redundant patterns can be eliminated at the evolution process, thus saving a large amount of the computation time.

The new codebook generation technique [13] was presented namely Thepade's Hartley Kekre's Error Vector Rotation (THKEVR) for generating the codebook efficiently. The proposed THtEVR algorithm was given fast changes in cluster orientation which was observed that more error reduction was obtained for images. The result shows the proposed THtEVR algorithm was given more reduction for the images having more edges.

A new framework was presented [4] for multi-layer representation of images where, instead of local-based processing, a global high dimensional vector representation of images was optimized successfully within various levels of reconstruction fidelity. The proposed approach was differed from conventional RQ framework which was based on k-means, the proposed RRQ along with pre-processing, randomly generates codewords from a regularized and learned distribution. The experimental result shows, the proposed approach was assured for different practical scenarios, e.g., when the acquisition devices at the query phase are much noisier than the enrollment cameras.

The two-level codebook generation algorithm [8] was presented to reduce the mean square error (MSE) for the codebook size. The new novel idea was presented to split the codebook in two levels in the ratio L1:L2. Any codebook can be used for level 1 and the error image was determined. On this error image same VQ algorithm was utilized in level 2. It was realized that this method was drastically reduced MSE as compared to allocate of entire codebook to level 1. Minimum MSE was obtained by this algorithm was depend on ratio L1:L2 and the image were dependent. However size allocation in the ratio of 1:1 for level 1 and level 2 on the average gives the best results reducing MSE for the size of the codebook. Further it was observed that MSE reduction obtained using KPE codebook with respect to LBG.

The K-means algorithm was presented [7] for optimization of codebook. The K-means is an optimization algorithm but this algorithm was taken very long time to converge. In order to overcome this issue, Linde Buzo and Gray (LBG) and Kekre's Fast Codebook Generation (KFCG) algorithms were utilized. It was observed that the minimum error obtained from both LBG and KFCG codebooks was almost same indicating that there was a unique minima. The result shows the KFCG codebook was taken lesser number of iteration compared to LBG codebook. This indicated that KFCG codebook was closer to the optimum.

III. PROPOSED METHODOLOGY

In this section, enhance the performance of generalized residual vector quantization (EGRVQ) to generate the codebook book optimally for achieving the image compression. The EGRVQ is performed codebook optimization on all zero codebook on each phase.

Generalized Residual Vector Quantization (GRVQ)

The GRVQ is learnt effective encoding with additive model. The GRVQ is optimized the codebooks of zero vectors to learn from scratch. Formally, denote the encoding of $X \rightarrow (i_1(x), i_2(x), \dots \dots \dots \dots \dots, i_m(x))$, the current residual of x is

$$e_x = x - \sum_{m=1}^{M} c_m\,(i_m(x)) \quad (1)$$

On each iteration, GRVQ randomly pick an m-th codebook $C_m = \{c_m(1), \dots\dots\dots, c_m(K)\}$ to optimize. Initially, performing incremental clustering on an intermediate codebook, defined as

$$\chi' = \{x' | x' = e_x + c_m(i_m(x)), x \in \chi\} \quad (2)$$

Then optimize the codebook with the following objective function

$$\min_{c_m(.),\, i(.)} \frac{1}{N} \sum_{x' \in \chi'} \left\| x' - c_m(i(x')) \right\|^2 \quad (3)$$

Finally, re-encode the original χ with the optimized codebook C_1,........,C_k and obtain the residual vectors for the next iteration.

Enhanced Generalized Residual Vector Quantization (EGRVQ)

In this section, the performance of generalized residual vector quantization (EGRVQ) is further enhanced for generating the optimal codebook. The EGRVQ is performed generalized vector quantization with higher accuracy. The EGRVQ is performed in to three phases which are transition clustering, multipath encoding and ∈-term elimination.

In a transition clustering phase, the k-means algorithm is presented in conventional GRVQ which was suffered convergence to local minimum. To overcome is issue; the Non-negative Matrix Factorization (NMF) clustering algorithm is presented in proposed EGRVQ to optimally reduce the size of codebook. The computation error of codebook is reduced in the multipath encoding phase. For elimination of ∈-term, the Euclidean distance computation was performed in conventional GRVQ which was suffered by computational complexity. In the proposed EGRVQ, the mahalanobis distance Computation is presented for achieving optimal quantization accuracy.

Transition Clustering

In this section, the Non-Negative Matrix Factorization (nmf) clustering algorithm is presented to optimally reduce the size of codebook. The NMF is a low rank approximation technique which initiates the constraint that the data matrix and the factorizing matrices are non-negative. By allowing only additive linear combinations of components with nonnegative coefficients, NMF inherently leads to a parts-based representation. The NMF is a holistic representation model which leads to a much more intuitive and interpretable representation.

Formally, NMF is characterized by the following factorization

$$X \approx WH \quad (4)$$

Where X, W, H ≥0, X∈ R^{mXn}, W∈ R^{mXk}, H ∈ R^{kXn} and k is the number of components (the rank) in which the data matrix will be represented. Naturally, it makes sense that k < min (m, n).

The approximation problem presented in (4) is often formulated as an optimization problem of the form

$$\min_{W,H \geq 0} D\,(X \| WH) \quad (5)$$

Where D (A‖B) is a divergence function. The divergence is the Euclidean distance between X and WH, in which case the optimization problem becomes

$$\min_{W,H \geq 0} \|X - WH\|_F^2 = \sum_{i,j} (X - WH)_{ij}^2 \quad (6)$$

In order to construct the implications of NMF, assume each column of X is an image of x pixels. Then, using the approximation X ≈WH, one say that the columns of W correspond to a basic image. Each column of H on the other hand, corresponds to an encoding of each image in terms of the basic images.

Nonnegativity constraints on X, W and H implicitly make for a more interpretable and parts based representation of the data. W, H ≥ 0 implies that each element $X_{ij} = w_i h_j^T$ is a weighted addition of positive vectors. By limiting both the basis and the encoding to nonnegative values, NMF forces the factorization to an additive weighted structures (encoding) of non-negative building blocks (bases). In turn, the non-negativity in NMF implies that its use is constrained to cases where the data matrix is composed of non-negative elements.

Multi-Path Encoding

In this section an efficient beam search method is presented for GRVQ-APOA optimized codebooks. Denote $X \to (i_1, i_2, \dots\dots\dots, i_M)$ as the optimal encodings for X, which quantizes x ≈ $\sum_{m=1}^{M} c_m\,(i_m)$ minimizing the quantization error $E = \|x - \sum_{m=1}^{M} c_m\,(i_m(x))\|^2$. Suppose know the first (n-1) optimal encodings $(i_1, i_2, \dots\dots\dots, i_{n-1})$. In order to determine the n-th optimal encoding i_n effectively, denote $\hat{x} = \sum_{m=1}^{n-1} c_m(i_m)$ and $\tilde{x} = \sum_{m=n+1}^{M} c_m\,(i_m)$ and consider quantization error E as a function of i_n

$$E = \|x - (\hat{x} + c_n(i_n) + \tilde{x}\|^2$$

$$= \|x - \hat{x} - \tilde{x}\|^2 + \|c_n(i_n)\|^2 - 2c_n(i_n)^T (x-\hat{x}) - 2c_n(i_n)^T\,\tilde{x} \quad (7)$$

In order to minimize the quantization error E, in equation (7) term $2c_n(i_n)^T\,\tilde{x}$ cannot be computed because $\tilde{x}$ is unknown to the encoding scheme, which leads to an error in estimating the best i_n. Low variance of $\tilde{x}$ is required for neglecting $2c_n(i_n)^T\tilde{x}$. A simple way to achieve this goal is rearranged the codebooks by the variance of code words in descending order. Generally, the GRVQ naturally produces code books descending order of variance of corresponding code words. This idea is utilized in the proposed beam search algorithm to encode a vector x. Then, sequentially encode x with each codebook and maintain a list of L best encodings of x. On each iteration, enumerate all possible code words on the next codebook, compute the distortion and determine the new L best encodings. This can be done efficiently with lookup tables.

When the EGRVQ is optimized as m-th codebook, there is no need to re-encode the vectors with the first (m-1) codebooks since the proposed methods is carried out sequentially and will obtain exactly the same first (m-1) encodings. This is varied from the encoding scheme, in which the change in any codebook requires re-encoding over all codebooks. The proposed encoding scheme is more efficient scheme, because required to consider one codebook at a time.

Eliminating ∈-term for efficient Mahalanobis distance computation

In this section, the Mahalanobis distance computation is presented to eliminate the ∈-term. The Mahalanobis distance (MD) is measured the distance between the two points in multivariate space. In a regular Euclidean space, variables (e.g. x, y and z) are represented by axes drawn at right angles to each other; the distance between any two points can be measured with a ruler.

The MD is a distance measure based on correlations between variables by which different patterns could be identified and analyzed with respect to a reference baseline. The MD measures is determined the similarity of the set of variables from an unknown sample to a set of values measure from a collection of known samples. One of the main applications of MD is introduced a scale based on all characteristics to measure the degree of abnormality. It measures the distances in multidimensional spaces taking into account the correlations between variables or characteristics that may exist. When compared to other multivariate measurement techniques such as the Euclidean distance, MD is superior. The Euclidean distance, for instance, does not indicate how well the unknown data set matches with the reference data set. MD is superior to the Euclidean distance because it takes into account the distribution of the points (correlation).

Moreover, Mahalanobis distances are based on both the mean and variance of the predictor variables, plus the covariance matrix of all the variables, and therefore take advantage of the covariance among variables. The region of constant Mahalanobis distance around the mean forms an ellipse in 2D space (i.e. when only 2 variables are measured) when more variables are used.

The Mahalanobis distances are calculated as

$$D^2 = (x - m)^T C^{-1} (x - m) \qquad (8)$$

Where

D^2 -Mahalanobis distance

x-vector of data

m-vector of mean values of independent variables

C^{-1}- Inverse Covariance matrix of independent variables

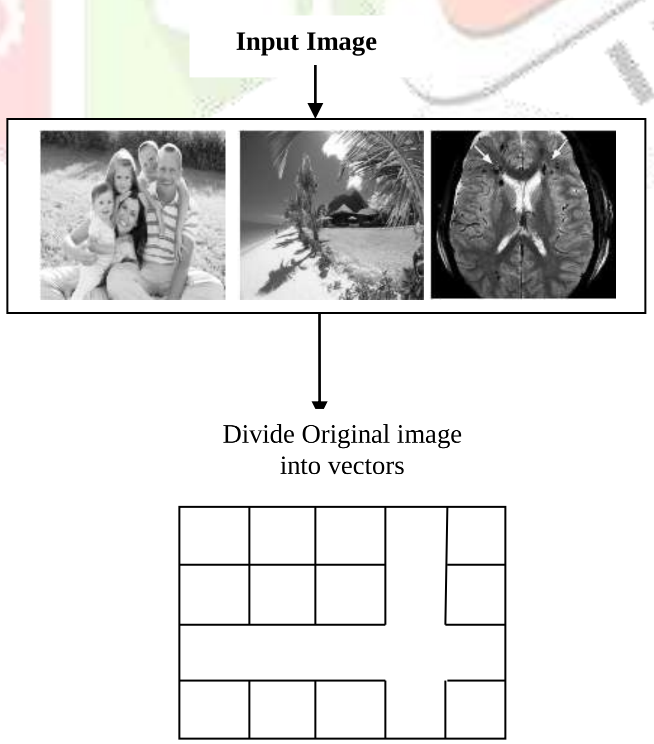
T- indicates vector should be transposed

Algorithm 1: Enhanced Generalized Residual Vector Quantization (EGRVQ)

Input: Number of codebooks M, containing N vectors, number of elements K per codebook, initial codebooks $C_m = \{c_m(1), \dots \dots \dots, c_m(k)\}, m \in [M]$.

Output: Optimized codebooks: $C_m : m \in [M]$

1. Repeat
2. Encode the optimized codebook with multipath encoding using Equation (7) and obtain the residual e_x defined in Equation (1).
3. Randomly pick a codebookC_m, generate a optimized codebook defined in (2).
4. Optimize C_m for Equation (8) by using transition clustering algorithm by using NMF clustering algorithm using Equation (6),
5. Until Quit condition.



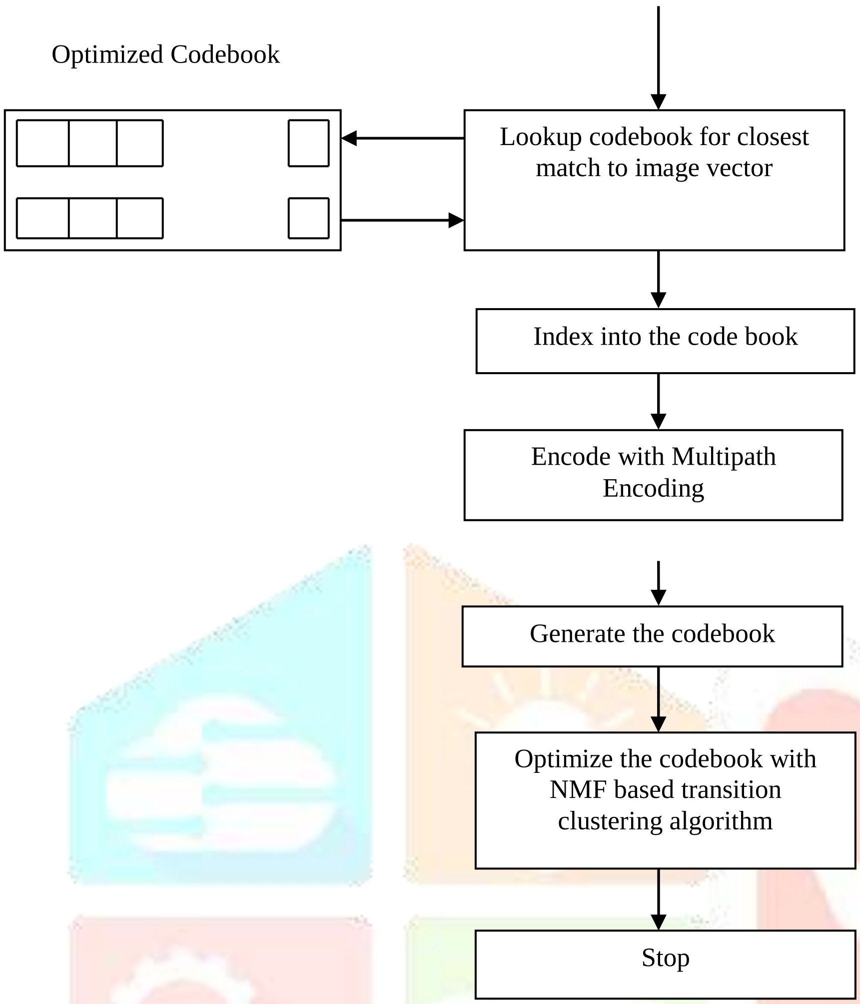
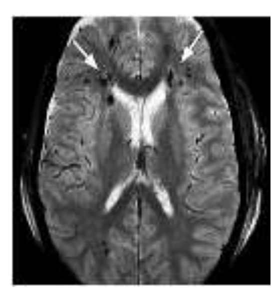


Figure 1 Proposed Architecture Diagram

IV. RESULT AND DISCUSSION

Experiments are conducted in MATLAB simulation and they are performed on three images such as family, nature and medical. The comparison is performed among APOA-GRVQ and proposed APOA-EGRVQ methods.

Methods/ Images	Family	Nature	Medical
Original Image			
APOA-GRVQ			

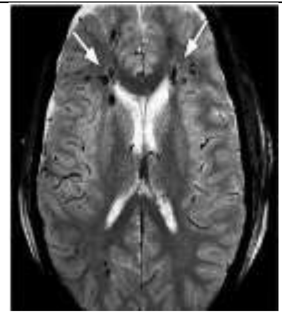
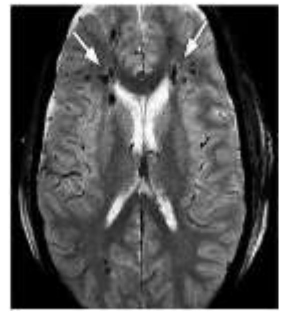
			
APOA-EGRVQ			

Figure 2 Comparison results of reconstructed image

Compression Ratio (C_R)

Compression Ratio is determined the data compression ability by finding the ratio between original image (C_1) and compressed image (C_2). It is defined by,

$$C_R\ (\%) = \frac{C_1}{C_2} \qquad (8)$$

Table 1 Comparison of Compression Ratio for family, nature and medical image

Images / Method	EXISTING	PROPOSED
	APOA-GRVQ	APOA-EGRVQ
Family	41.8846	44.0049
Nature	45.4231	49.1182
Medical	44.2142	45.4515

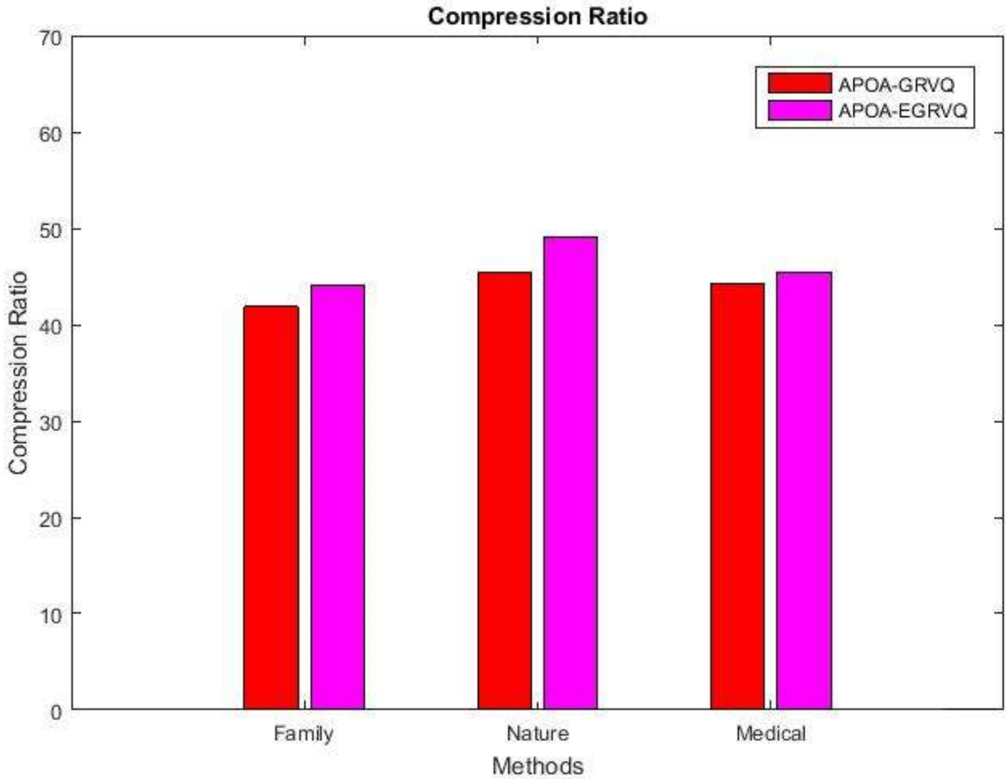


Fig 3 Comparison Result of Compression Ratio

Fig 3 shows the comparison results of existing APOA-GRVQ technique with proposed APOA-EGRVQ methods in terms of compression ratio. X axis is taken as various compression methods and Y axis is taken as compression ratio in percentage. From the bar chart the proposed APOA-EGRVQ method gives better high compression ratio for family, nature and medical image.

Structure Similarity

Structural similarity measure depends on the human visual system, that combines the structure, luminance and contrast information for assessing the visual quality of decompressed image.

Table 2 Comparison of structure similarity for family, nature and medical image

Images / Method	EXISTING	PROPOSED
	APOA-GRVQ	APOA-EGRVQ
Family	0.9164	0.9228
Nature	1.0414	1.2431
Medical	0.9241	0.9432

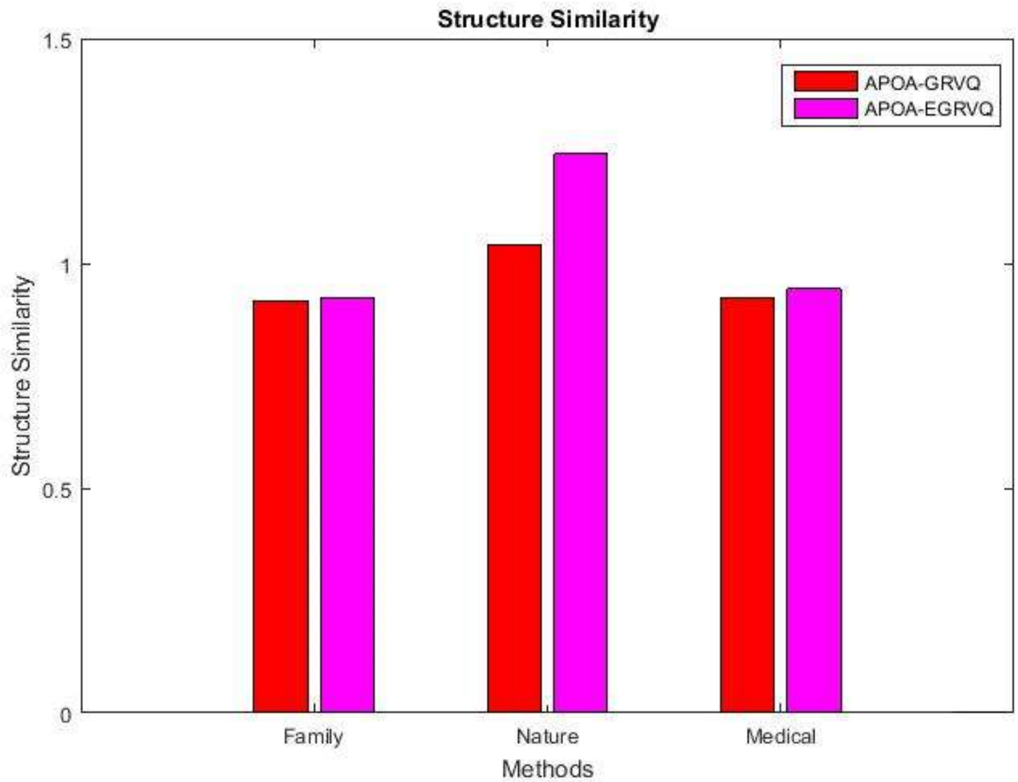


Fig 4 Comparison Result of Structure Similarity

Fig 4 shows the comparison results of existing APOA-GRVQ technique with proposed APOA-EGRVQ methods in terms of structure similarity. X axis is taken as various compression methods and Y axis is taken as structure similarity. From the bar chart the proposed APOA-EGRVQ method gives better high structure similarity for family, nature and medical image.

Peak Signal Noise Ratio (PSNR)

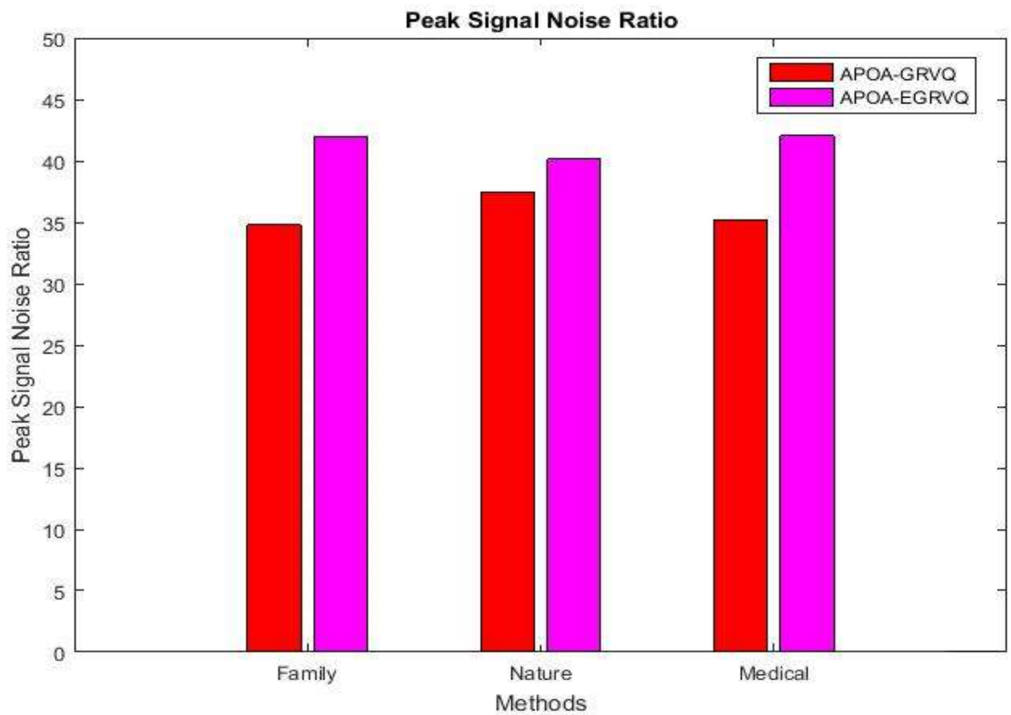
The PSNR is quality measurement between the original and a compressed image. The higher PSNR, value represents the best quality of the decompressed image.

$$\text{PSNR (dB)} = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (9)$$

R is the maximum peak pixel values of input image.MSE is mean square error between input and decompressed image.

Table 3 Comparison of Peak Signal Noise Ratio for family, nature and medical image

Images / Method	**EXISTING**	**PROPOSED**
	APOA-GRVQ	**APOA-EGRVQ**
Family	34.7935	41.9612
Nature	37.4321	40.1210
Medical	35.1425	42.0456



V.

VI. ***Fig 5 Comparison Result of Peak Signal Noise Ratio***

VII. Fig 5 shows the comparison results of existing APOA-GRVQ technique with proposed APOA-EGRVQ method in terms of peak signal noise ratio. X axis is taken as various compression methods and Y axis is taken as peak signal noise ratio values. From the bar chart, the proposed AOIC method gives better high peak signal noise ratio for family, nature and medical image.

Bit Rate (kb/s)

Amount of data processed in a given time is termed as Bit rate. The measurement of bit rate is bits per second, kilobits per second, or megabits per second.

Table 4 Comparison of Bit Rate for family, nature and medical image

Images / Method	**EXISTING**	**PROPOSED**
	APOA-GRVQ	**APOA-EGRVQ**
Family	8.7124	7.0906
Nature	8.4314	7.0882
Medical	8.0864	7.1207

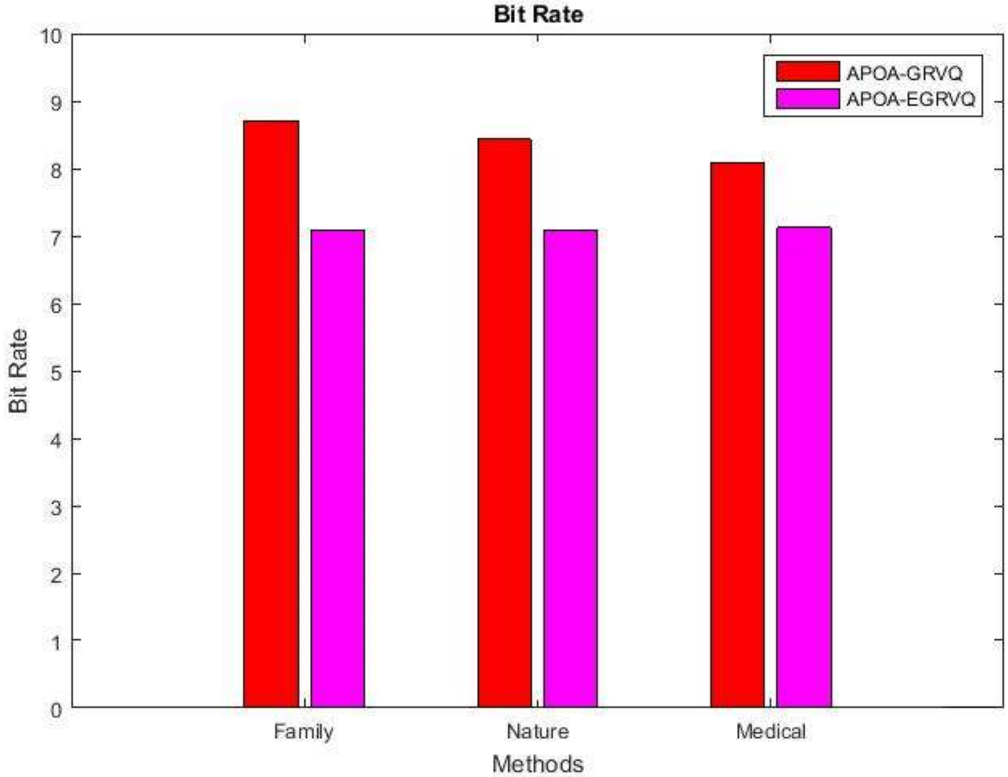


Fig 6 Comparison Result of Bit Rate

Fig 6 shows the comparison results of existing APOA-GRVQ technique with proposed APOA-EGRVQ methods in terms of Bit Rate. X axis is taken as various compression methods and Y axis is taken as Bit rate values. From the bar chart the proposed AOIC method gives better high bit rate for family, nature and medical image.

IV. RESULTS CONCLUSION

The proposed Enhanced GRVQ is efficiently optimized the codebook to increase the image quality with higher quantization accuracy. The EGRVQ is performed in the following ways. Initially, the NMF clustering algorithm is optimally reduce the size of codebook. The Multi-Path encoding is reduced the quantization error for both small and large size codebook. The mahalanobis distance Computation is presented to eliminate ∈-term in proposed EGRVQ for achieving optimal quantization accuracy. The performance of the proposed approach is demonstrated in terms of Compression Ratio, Peak-Signal Noise Ratio (PSNR), Structural Similarity, and Bit Rate.

REFERENCES

1. Chang, C. C., Li, Y. C., & Yeh, J. B. "Fast codebook search algorithms based on tree-structured vector quantization", Pattern Recognition Letters, 27(10), 1077-1086, 2006.
2. Divya, A.., and Sukumaran, S. "Image compression using generalized residual vector quantization", In Proceedings of the international conference on intelligent computing and control (I2C2), Volume (1), 357-362, 2017.
3. Feng, H. M., Chen, C. Y., & Ye, F. "Evolutionary fuzzy particle swarm optimization vector quantization learning scheme in image compression", Expert Systems with Applications, 32(1), 213-222, 2007.
4. Ferdowsi, S., Voloshynovskiy, S., & Kostadinov, D. "A multi-layer image representation using Regularized Residual Quantization: application to compression and denoising", arXiv preprint arXiv:1707.02194, 2017.
5. Horng, M. H., & Jiang, T. W. "The codebook design of image vector quantization based on the firefly algorithm", In International Conference on Computational Collective Intelligence (pp. 438-447). Springer, Berlin, Heidelberg, 2010.
6. Kekre, H. B., & Sarode, T. K. "An efficient fast algorithm to generate codebook for vector quantization", In Emerging Trends in Engineering and Technology, 2008. ICETET'08. First International Conference on (pp. 62-67). IEEE.
7. Kekre, H. B., & Sarode, T. K. "Vector quantized codebook optimization using k-means", International Journal on Computer Science and Engineering (IJCSE) Vol, 1, 283-290, 2009.
8. Kekre, H. B., & Sarode, T. "Two level vector quantization method for codebook generation using Kekre's proportionate error algorithm", International Journal of Image Processing, 4(1), 1-10, 2010.
9. Kotak, H. B., & Valaki, S. A "A Study of Image Compression Techniques and its Application in Telemedicine and Teleconsultation", Journal of Information, Knowledge and Research in Computer Science and applications, 3(1), 2014.

10. Khan, M. A., Mousa, W. A., & Khan, T. M. "Entropy-constrained reflected residual vector quantization: A realization of large block vector quantization", Optik-International Journal for Light and Electron Optics, 126(9-10), 888-897, 2015.
11. Liu, S., Shao, J., & Lu, H. "Generalized residual vector quantization for large scale data", arXiv preprint arXiv:1609.05345, 2016.
12. Tsai, C. W., Tseng, S. P., Yang, C. S., & Chiang, M. C. "PREACO: A fast ant colony optimization for codebook generation", Applied Soft Computing, 13(6), 3008-3020, 2013.
13. Thepade, S. D., Mhaske, V., & Kurhade, V. "Thepade's Hartley Error Vector Rotation for Codebook Generation. In Vector Quantization", In Advances in Computing, Communications and Informatics (ICACCI), 2013 International Conference on (pp. 2007-2012). IEEE, 2013.

AUTHORS

A.Divya received the Bachelor of Computer Science (B.Sc.) degree from the Bharathiar University, in 2012. She done her Master of Computer Science (M.Sc) degree in Bharathidasan University in 2014 and she awarded M.Phil Computer Science from the Bharathiar University, Coimbatore, in 2015. Currently she is doing her Ph.D Computer Science in Erode Arts and Science College. Her Research area includes Digital Image Processing.

Dr. S. Sukumaran graduated in 1985 with a degree in Science. He obtained his Master Degree in Science and M.Phil in Computer Science from the Bharathiar University. He received the Ph.D degree in Computer Science from the Bharathiar University. He has 28 years of teaching experience starting from Lecturer to Associate Professor. At present he is working as Associate Professor of Computer Science in Erode Arts and Science College, Erode, Tamilnadu. He has guided 6 Ph.D Scholars and more than 55 M.Phil research Scholars in various fields. Currently he is Guiding 5 M.Phil Scholars and 8 Ph.D Scholars. He is member of Board studies of various Autonomous Colleges and Universities. He published around 68 research papers in national and international journals and conferences. His current research interests include Image processing and Data Mining, Networking.