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Implementation of Image Quality and Design Time for Block-based Lossy VQ Image Compression using K-Means and K-Medoids Algorithm in Spatial Domain

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Abstract— **Data Mining (DM) technologies are one of the vast and hot topics in today's era. In the digital and computing world, information is generated and collected at a rate that rapidly exceeds the boundary range. It is increasing significantly in bio-medical, bio-informatics, engineering and health-care research. Large amount of biological and clinical data have been generated and collected at an unprecedented speed and scale. It seems to be a big disadvantage during storage and transmission. It raises the problem of reducing the memory size of a digital image. This research has focused on the lossy Vector Quantization (VQ) image compression to reduce the data volume in the spatial domain. We are using two unsupervised clustering algorithm for lossy VQ technique such as K-Means and K-Medoids. These two algorithms are proposed to analyze the performance in data mining and to other applications. To evaluate the clustering quality in image compression, the distance between two data points are taken for analysis. For two unsupervised clustering techniques, different block size are used as 4x4 (16) and 8x8 (64) with the codebook size of 25 and 50 in this research paper. In spatial domain, K-Medoids was compared with K-Means in terms of execution time and quality (PSNR). The research results show that the K-Means algorithm yields the best results compared with K-Medoids algorithm.**

Index Terms—**Data Mining, K-Means, K-Medoids, Vector Quantization, Spatial domain, SNR, PSNR.**

I. Introduction

Now-a-days, studies on image compression techniques are very common in terms of lossless and lossy compression. In addition, error-free reconstruction of the original image may be impossible in many cases for lossy compression. Consequently, lossy compression may produce an acceptable error that does not affect much on the original image. This can be seen in fast transmission of still images over the Internet where the amount of error can be acceptable [1] [2].

In previous studies, lossy image compression method using K-Means clustering algorithm [3] has been proposed. This approach has enabled to compress an image to 75%, when the compressed image is visually 95% similar to the original image. Image processing and analysis applied to nuclear medicine images for diagnosis, improve the acquired image qualitatively as well as offer quantitative information data which is useful in patient's therapy and care.

Data Mining (DM) is the extraction of information from larger datasets to facilitate it's usage for real time applications. DM has a variety of algorithms for data analysis such as Clustering, Association, Classification, etc. There are numerous types of unsupervised clustering algorithm such as Partitioning, Hierarchical, Grid-based and Model-based methods. This research is focused on the Partitioning based clustering. However, it generates a partition of the data such that objects in a cluster are more similar to each other than they are to objects in other clusters. The K-Means and K-Medoids unsupervised clustering algorithm are examples of partitional methods.

In the advent of World Wide Web search engines, the concept of clustering is used as an intermediate compression tool. First, the data is clustered and then only the clusters' representatives are used for the analysis part. But this research work discusses about the quality and computational complexity of K-Means and K-Medoids algorithm in spatial domain. Regarding K-Means and K-Medoids clustering algorithm, arbitrarily image compression data points are given as input for clustering analysis.

The organization/outline structure of the rest of this research paper is as follows. In section 2, the concept of Spatial domain are discussed. In section 3, the basic concept and methodology of K-Means algorithm are discussed. Another, the basic concept and methodology of K-Medoids algorithm are discussed in section 4. Research experimental results are discussed in section 5. Finally, section 6 contains the Conclusion and Future work.

II. K-Means Algorithm

K-Means is an unsupervised fast search clustering algorithm. This algorithm also come under classical partitioning technique. However, it is also one of the standard algorithm used for lossy VQ image compression in Spatial domain. It follows a simple way to classify a given data set through a certain number of clusters. The main idea behind K-Means Algorithm is to define 'K' centroids, one for each cluster. These centroids should be placed in the best way so they are far away from each other as much as possible. This research work poses a serious concern which initiated the development of robust strategies for fast convergence of K-means using image compression for block and codebook size for that image. It is a fast search clustering algorithm by reduction of the number of candidate blocks for matching

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[4][5]. However, it also reduce computational complexity of the matching criteria [6][7].

The steps of the K-means algorithm are:

1. Initialization: Randomly 'K' data points are chosen to initialize the cluster centers.
2. Nearest-neighbor search: Each data point is assigned to the cluster center that is closest to it. The distance from the data vector to the centroid is calculated as:

$$d(z_p, a_j) = \sqrt{\sum_{K=1}^{d} (z_{pK} - a_{jK})^2} \qquad (1)$$

Where d is the dimension of the data vector, zp is the centroid of cluster p and aj is the data vector for object 'j'.

3. Mean update: New cluster centers are calculated finding the mean of the input vectors assigned to a particular cluster.
4. Stopping rule: repeat steps 2 and 3 until no more change in the value of the means

One of the disadvantages of K-Means Algorithm is to ignore measurement errors, or uncertainty, associated with the data and it is also known as Error based Clustering.

2.1 Methodology of K-means using VQ in spatial domain.

There are following steps based on Figure 1 which are:

Step 1: Read Bridge or Boat image of 256x256 and convert it to gray-scale level.

Step 2: Initialization of the size of block 'B' and size of codebook 'C' for different scenarios

Step 3: Quantizing K-Mean clustering for an image

There are 4 sequences to quantizing K-Mean clustering for an image:

(a) Initialize a set of training vectors 'nt' and we need a codebook of size 'C'.

(b) Second sequence is to randomly choose 'M' dimensional or block vectors as the initial set of codewords in the codebook.

(c) Third sequence is to search for nearest neighbor for each training vector. This will allow finding the codeword in the current codebook which seems to be the closest in terms of spectral distance and assign that vector to the corresponding cell.

(d) Finally update the Centroid for the codeword in each cell using the training vectors assigned to that cell. Repeat sequence 2 and 3 again and again until the procedure converges or Average distance falls below a preset threshold.

Step 4: Compute reconstructed image using Table look-up decoding process in spatial domain

Step 5: Implementation of performance metrics such as Bit rate, CR, SNR, MSE, and PSNR for reconstructed based on one of the following scenarios.

Step 6: Check the execution time of all the scenarios for reconstructed image depending on the size of block and codebook.

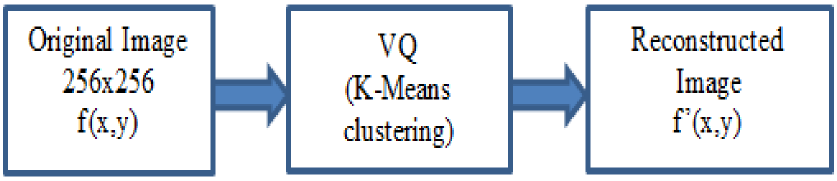


Figure 1. Spatial domain using VQ with K-Means clustering

III. K-MEDOIDS

K-Medoids is a classical partitioning technique of clustering that clusters the data set of 'r' objects into 'K' number of clusters [8] [9]. It is to find 'K' clusters in 'r' objects by first arbitrarily finding a representative object (the Medoids) which is the most centrally located object in a cluster, for each cluster. This K-Medoids algorithm is often called as Representative Object Based algorithm. K-Medoids clustering [10] uses medoids to represent the clusters rather than using conventional mean/centroid. K-Medoids algorithm operates on the principle of minimizing the sum of dissimilarities between each object and its corresponding reference point.

Input: K: The number of clusters; d: A data set containing 'r' objects

Output: A set of k clusters that minimizes the sum of the dissimilarities of all the objects to their nearest medoid.

3.1 Methodology of K-Medoids using VQ in spatial domain.

Step 1: Read Bridge or Boat image of 256x256 and convert it to gray-scale level.

Step 2: Initialization of the size of block 'B' and size of codebook 'C' for different scenarios.

Step 3: Quantizing K-Medoids clustering for an image

(a) Select 'N' points as the initial representative objects

(b) Repeat

(i) Assigning each point to the cluster with the closest medoids

$$\mathrm{cost}(r,c) = \sum_{i=1}^{d} |r_i - c_i| \qquad (2)$$

Where 'r' represents data objects and 'c' represents medoids of clusters

(ii) Randomly select a non-representative object 'Oj'

(iii) Compute the total cost 'TC' of swapping the medoid 'c' with object 'Oj'

$$\text{TC=current total cost - past total cost} \qquad (3)$$

(iv) if TC<0, then swap 'c' with 'Oj' to form the new set of medoids

Until convergence criterion is satisfied

Step 4: Compute K-Medoids reconstructed image using Table look-up decoding process in spatial domain

Step 5: Implementation of performance metrics such as PSNR and execution time for reconstructed K-Medoids depending on the size of block and codebook.

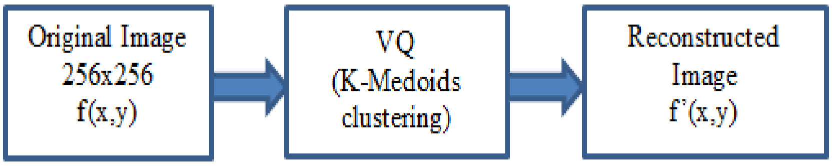


Figure 2. Spatial domain using VQ with K-Medoids

IV. Difference between K-Medoids and K-Means

- K-Medoid is based on minimizing the absolute distance between the points and the selected centroid, whereas K-Means is based on minimizing the Euclidean square distance.
- K-Means is sensitive to outliers than K-Medoids because a mean is easily influenced by extreme values.
- K-Means uses the mean point as the center of a cluster while K-Medoids uses an actual point in the cluster to represent it.
- K-Medoid is the most centrally located object of the cluster as compared to K-Means.
- K-Means cannot represent the correct cluster center where as K-Medoid represents the cluster center.

V. Results

5.1 Results of K-means using VQ in spatial domain.

Table 1 shows the data for Bridge images of K-Means using VQ in Spatial domain. The detailed information in the Table 1 represents different block size used as 4x4 (16), 8x8 (64), 16x16 (256), and 32x32 (1024) with codebook size of 25 and 50. By using these block and codebook sizes, different performance metrics have been calculated to check the quality of the Bridge image.

Table 1.
Bridge image of K-Means VQ in Spatial domain

Image 256x256	Bit Rate	Compression Ratio (CR)	SNR	PSNR	MSE	Execution Time
1024x25	0.0045	$1.7641x10^3$	18.0256	21.129	2770.96	6.8045
1024x50	0.0055	$1.4515x10^3$	18.9541	21.550	2702.45	7.5149
256x25	0.0181	441.0128	19.8573	22.651	2691.32	8.7968
256x50	0.0220	362.8725	20.5265	23.249	2506.66	10.410
64x25	0.0726	110.2532	21.4792	24.952	2476.58	12.0607
64x50	0.0882	90.7181	21.9804	25.480	2419.35	12.5786
16x25	0.2902	27.5633	23.5684	27.236	1401.67	30.9942
16x50	0.3527	22.6795	24.8823	29.029	1395.29	32.2150

From Table 1 it is evident that block size of 16 and codebook size of 50 shows the best SNR and PSNR, but higher execution time due to larger number of blocks (4096 blocks) as compared to other parameters.

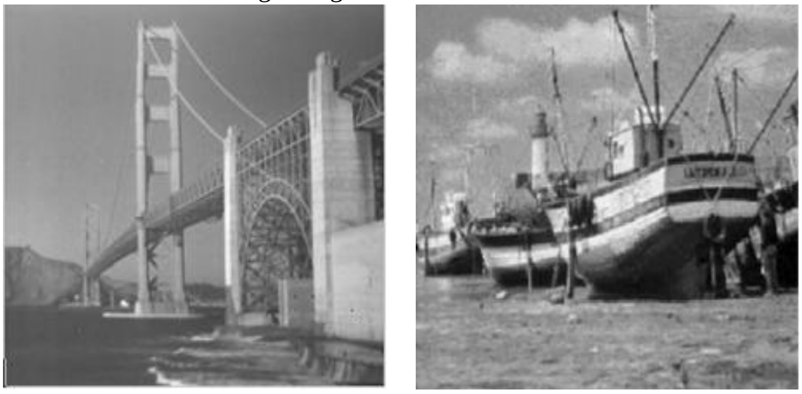
Table 2 shows the data for Boat images of K-Means using VQ in Spatial domain. The detailed information in the Table 2 represents different block size used as 4x4 (16), 8x8 (64), 16x16 (256), and 32x32 (1024) with codebook size of 25 and 50.

Table 2.
Boat image of K-Means VQ in Spatial domain

Image 256x256	Bit Rate	Compression Ratio (CR)	SNR	PSNR	MSE	Execution Time
1024x25	0.0045	$1.7641x10^3$	18.986	21.667	2720.43	6.604
1024x50	0.0055	$1.4515x10^3$	19.939	22.480	2646.25	7.414
256x25	0.0181	441.0128	20.312	23.327	2598.72	8.468
256x50	0.0220	362.8725	20.893	24.644	2444.81	10.111
64x25	0.0726	110.2532	21.993	25.955	2250.66	11.807
64x50	0.0882	90.7181	22.733	27.488	2232.43	12.278
16x25	0.2902	27.5633	23.961	28.167	1390.02	29.599
16x50	0.3527	22.6795	25.384	29.913	1382.44	31.161

From Table 2 it is evident that block size of 16 and codebook size of 50 shows the best SNR and PSNR, but higher execution time as compared to other parameters. The objective is to get the best quality-acceptable image which is 16x50 in this Table 2. In fact, 16x50 for Boat image in Table 2 has higher SNR and PSNR than 16x50 for Bridge image in Table 1. There is a trade-off between PSNR and CR for lossy VQ in spatial domain. Moreover, CR is inversely proportional to the PSNR for different block and codebook sizes scenarios as shown in Table 1 and Table 2.

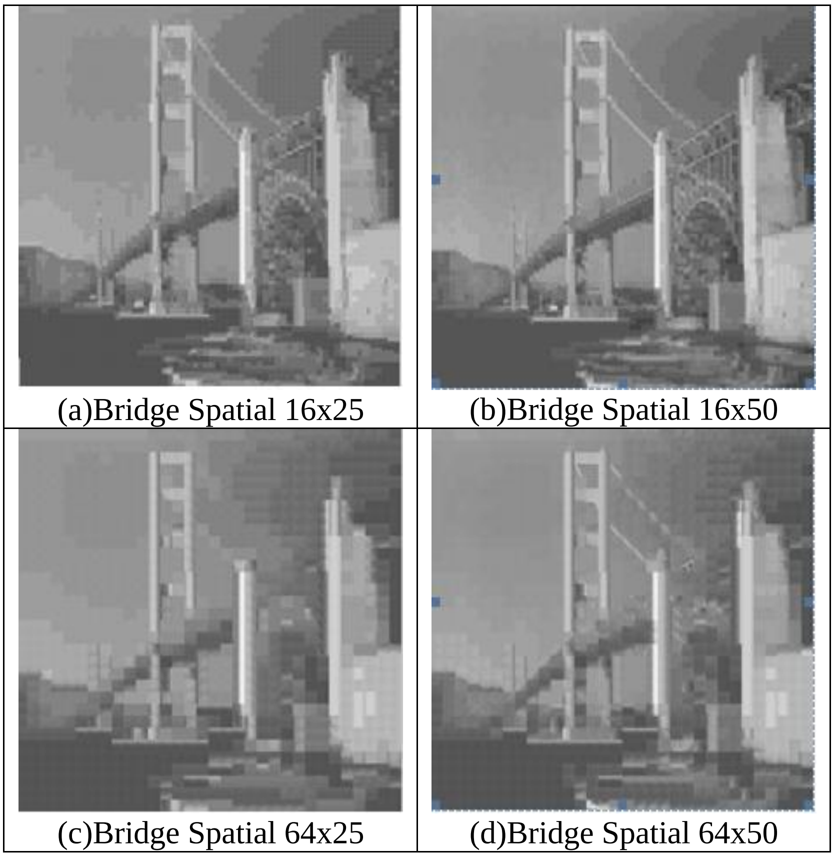
Original Bridge and Boat image are shown in Figure 3 (a) and Figure 3 (b).



(a) Bridge image (b) Boat image

Figure 3. Original Bridge image and Boat image

Figure 4 (a), (b), (c) and (d) represents the reconstructed Bridge image for block size of 16 and 64 with codebook size of 25 and 50 in spatial domains.

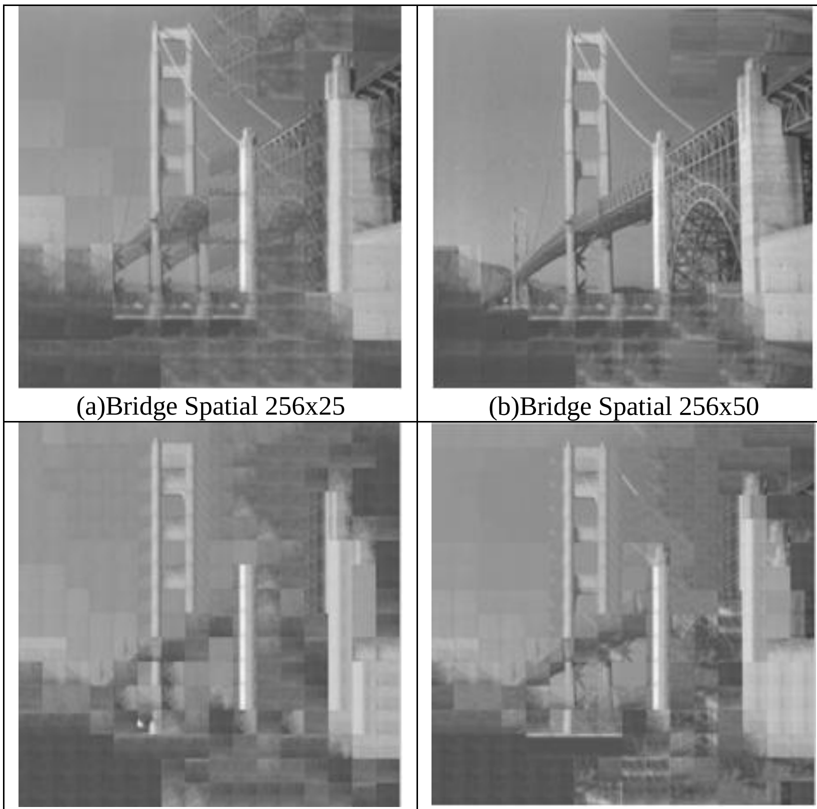


(a)Bridge Spatial 16x25 (b)Bridge Spatial 16x50

(c)Bridge Spatial 64x25 (d)Bridge Spatial 64x50

Figure 4. Bridge image of block 16 and 64 with codebook of 25 and 50 in spatial domain

Figures 5 (a), (b), (c), and (d) represents the reconstructed Bridge image for block size of 256 and 1024 with codebook size of 25 and 50 in spatial domains.



(a)Bridge Spatial 256x25 (b)Bridge Spatial 256x50

(c)Bridge Spatial 1024x25 (d)Bridge Spatial 1024x50

Figure 5. Bridge image of block size of 256 and 1024 with codebook size of 25 and 50 in spatial domain

From these Figures 4 (a)-(d) and Figures 5 (a)-(d), Figure 4 (b) of 16x50 (block size of 16 and codebook size of 50) shows higher SNR and PSNR to get the best quality-acceptable image than other Figures in spatial domain. As, an example, Figure 5 (c) and 5 (d), 1024x25 and 1024x50 reconstructed image gives very high CR, but low SNR, low PSNR, high MSE, and less execution time than all Figures 4 (a)-(d) and Figures 5 (a)-(b). Of course, the exact performance may vary among individual image in spatial domain. But these results from Tables 1 & 2 and Figures 4 & 5 indicate a trend. Smaller block size and bigger codebook size will produce a superior image quality, at the cost of lower CR in spatial domain.

5.2Results for K-Medoids in spatial domain.

Table 3 shows the data of K-Medoids for Bridge and Boat images in Spatial domain.

Table 3.
PSNR and Execution Time for Bridge and Boat K-Medoid in Spatial Domain

Image 256x256	K-Medoids Bridge PSNR	K-Medoids Bridge Execution Time	K-Medoids Boat PSNR	K-Medoids Boat Execution Time
64x25	24.118	14.223	24.997	13.116
64x50	25.046	15.631	26.045	14.725
16x25	26.448	32.546	27.411	31.554
16x50	28.112	34.521	29.236	33.612

From Table 3 it is evident that block size of 16 and codebook size of 50 shows the best PSNR, but higher execution time due to larger number of blocks (4096 blocks) as compared to other parameters. In terms of getting higher PSNR, block size of 16 and codebook size of 50 for Boat image shows less execution time of 33.61 seconds as compared to the block size of 16 and codebook size of 50 for Bridge image with more execution time of 34.52 seconds.

Execution time comparison between K-Medoids and K-Means in spatial domain for Bridge image is used for block size of 16 and 64 in Table 4.

Table 4.
Execution Time Comparison for Bridge image between K-Medoids vs. K-Means in Spatial Domain

Image size 256x256	16x25	16x50	64x25	64x50
K-Means	30.9942	32.215	12.0607	12.5786
K-Medoids	32.546	34.521	14.223	15.631

From Figure 6, it can be seen that K-Medoids takes more execution time as compared to K-Means for Bridge image in spatial domain. In fact, K-Means (from previous Table 1 results) has a higher PSNR than the K-Medoids in spatial domain.

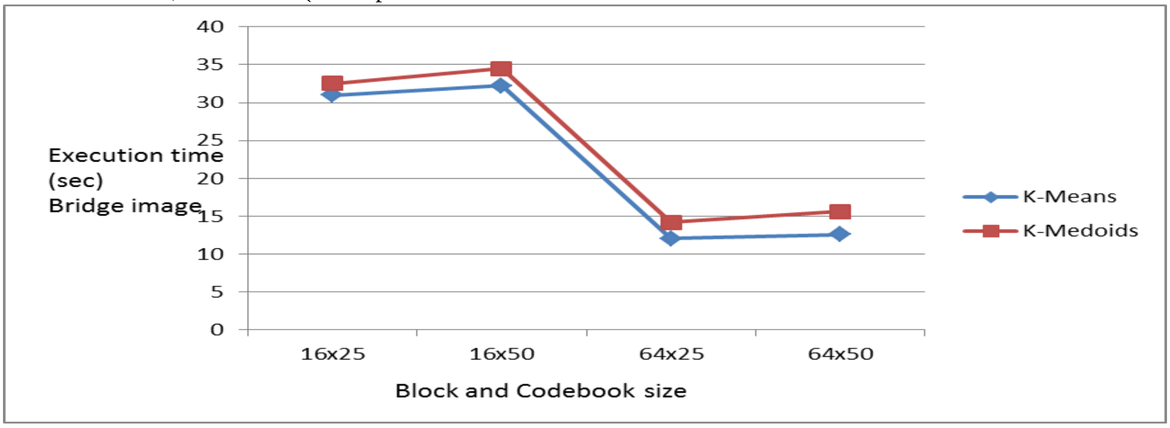
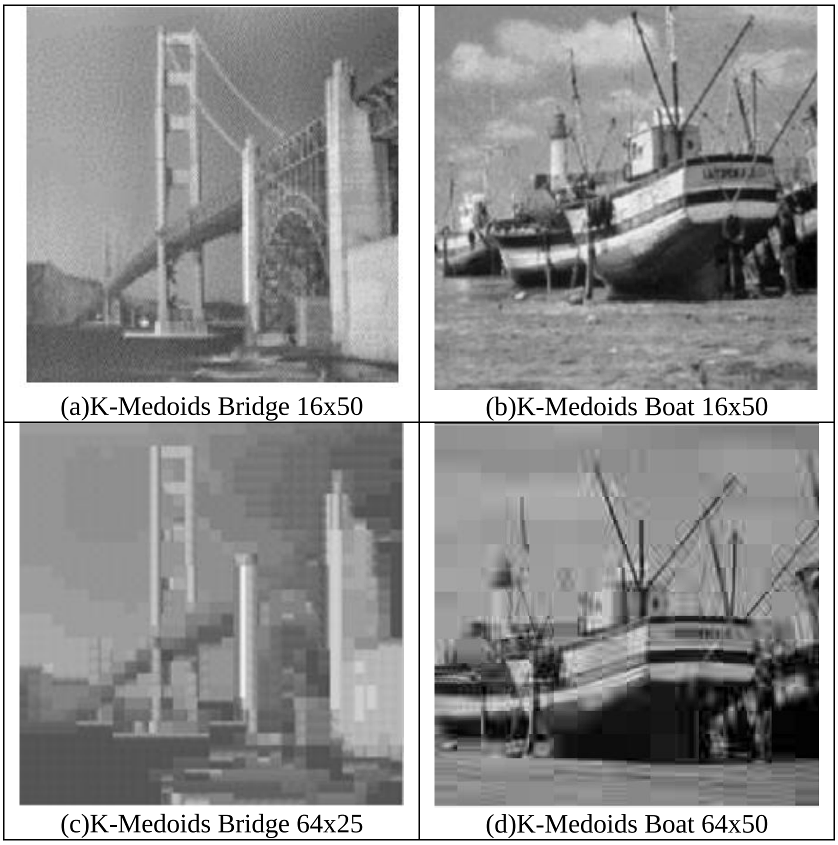


Figure 6. Execution time comparison between K-Medoids and K-Means in spatial domain.

Figure 7 (a)-(d) represents the reconstructed images for K-Medoids in spatial domain. Figure 7 (a) represents the reconstructed K-Medoids Bridge image for a block size of 16 with codebook size of 50. Figure 7 (b) represents the reconstructed K-Medoids Boat image for a block size of 16 with codebook size of 50. Figure 7 (c) represents the reconstructed K-Medoids Bridge image for a block size of 64 with codebook size of 25. Figure 7 (d) represents the reconstructed K-Medoids Boat image for a block size of 64 with codebook size of 50.



(a)K-Medoids Bridge 16x50
(b)K-Medoids Boat 16x50
(c)K-Medoids Bridge 64x25
(d)K-Medoids Boat 64x50

Figure 7. K-Medoids reconstructed Bridge and Boat image in spatial domain

From these Figures 7 (a)-(d), Figure 7 (b) of 16x50 (block size of 16 and codebook size of 50) shows very higher PSNR to get the best K-Medoids quality-acceptable image than other Figures in spatial domain. As an example, Figure 7 (c) and 7 (d), 64x25 and 64x50 reconstructed K-Medoids image has very low PSNR and takes less execution time than other Figures 16 (a)-(b).

VI. PERFORMANCE METRICS

Following performance metrics are used for advanced VQ techniques.

6.1 Lossy compression.

(a) Bit Rate. It is defined as:

$$\text{Bit Rate} = \frac{\text{Number of bits to index a codeword vector}}{\text{Number of samples in a vector}}$$

$$\text{Bit Rate} = \frac{\log_2 C}{B} \qquad (4)$$

'B' is the block size and 'C' is the codebook size. The units for Bit Rate are bits/pixel.

(b) Compression Ratio (CR). It is defined as:

$$\text{Compression Ratio} = \frac{\text{Original Bit Rate}}{\text{New Bit Rate}} \qquad (5)$$

(c) MSE. MSE (Mean Square Error) represents the cumulative squared error between the reconstructed 'y' and the original image 'x'.
'm' represents the index in a row in digital image. 'M' represents Number of rows of digital image.'n' represents the index in a column in digital image. 'N' represents Number of columns of digital image.
It is given by

$$\text{MSE} = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[|y(m,n) - x(m,n)|^2]}{(MN)} \qquad (6)$$

(d) SNR. SNR (Signal to Noise Ratio) is defined as:

$$\text{SNR} = \frac{10\log\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x^2(m,n)\right)}{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[[y(m,n) - x(m,n)]^2]} \qquad (7)$$

(e) PSNR. PSNR (Peak Signal to Noise Ratio) is a popular term for the ratio between maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its MSE representation. PSNR is usually expressed in terms of the logarithmic Decibel (dB) scale.

$$\text{PSNR} = \frac{10\log(256)^2}{\text{MSE}} \qquad (8)$$

(f) Execution Time (sec). Execution time is calculated by MATLAB built-in routine called as 'tic-toc'. It is to call 'tic' before we run the program and 'toc' afterwards.

VII. CONCLUSION

When images are converted from one form to another by such processes as imaging, scanning, or transmitting; the quality of the output image may be degraded but still acceptable to the users [11]. It stimulates the need to develop some efficient and effective techniques which are used to deal with this huge amount of data [12].

From our results, K-Medoids has a low PSNR and also takes more execution time than K-Means in spatial domain. K-Medoids takes more iterations and it also having complexity issues. In our data, there is no outlier so K-Mean algorithm is the best choice in spatial domain in this research paper. Future work will be the comparison of K-Means with other unsupervised algorithms in spatial domain.

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