# Constrain Study of Basic Vector Quantization Techniques for Image Compression

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## ABSTRACT
Vector Quantization (VQ) is one of the lossy image compression techniques. VQ comprises of three different entities: codebook generation, image encoding and image decoding. In this paper three different VQ techniques namely Mean Remove Vector Quantization (MRVQ), Shape Gain Vector Quantization (SGVQ) and Classified Vector Quantization (CVQ) has been discussed and their performance in terms of Signal to Noise ratio (SNR) is compared. Lloyd algorithm is used for optimal codebook generation.

## Keywords
Classified VQ, Lloyd"s Algorithm, Mean removed VQ, Shape Gain VQ.

## 1. INTRODUCTION
Multimedia is rapidly becoming the dominant technology of the information age. Storing and transmitting the digital image component of multimedia systems is a major problem. The amount of data required to present images at an acceptable level of quality is extremely large. Compression is utilized to reduce the quantity of data whilst preserving acceptable image quality. Algorithms for compression invariably utilize rectangular partitioning of the image, which is counter-productive for real-world images that contain smooth edges and textures. On the assumption that computing power is not the limiting factor, this Paper involves the investigation of several techniques for circumventing the partitioning problem using real and synthetic images. A description of some experimental evaluations of these techniques, which show encouraging results, has been presented in this paper.

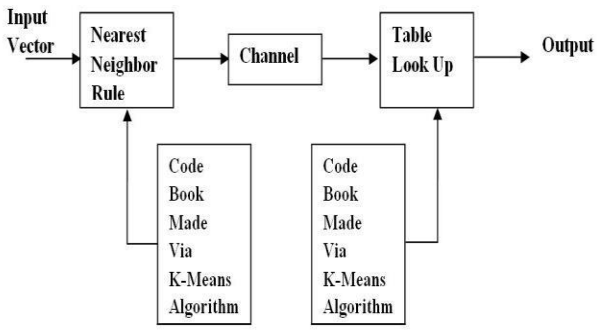


**Fig 1: Block diagram of Vector Quantization**

A literature search was undertaken to investigate as many compression methods as possible. From this search, Vector Quantization (VQ) was deemed to be the compression method of choice to be pursued. Vector Quantization is a pattern matching process ideally suited for coding digital images in a compact form. A number of different VQ algorithms were implemented and evaluated against pre-existing compression techniques.

A vector quantizer Q of dimension k and size N is a mapping from a point in k-dimensional Euclidean space, Rk into a finite set C containing N output or reproduction points that exist in the same Euclidean space as the original point. These reproduction points are known as code words and these set of code words are called a codebook C with N distinct code words in the set. Thus the mapping function Q is defined as,

$$Q: Rk \rightarrow C \quad (1)$$

The rate of the vector quantizer or the number of bits used to express each quantized vector is,

$$R= (\log N)/k \quad (2)$$

This rate equation is very useful as it gives the amount of compression one can expect for a particular VQ coding scheme. Vector quantization in its entirety is quite a simple concept. The major complexity comes about in selecting a codebook C of size N that best represents original vectors or training set X in Rk Euclidean space. To solve this optimization problem one requires a distortion measure d(x; x) that represents the penalty of the mapping Q process.

## 2. PROCEDURE

### 2.1 Lloyd Algorithm
In computer science and electrical engineering, Lloyd„s algorithm, also known as Voronoi 26 iteration or relaxation, is an algorithm for grouping data points into a given number of categories, used for k-means clustering. Lloyd„s algorithm is usually used in a Euclidean space, so the distance function serves as a measure of similarity between points, and averaging of each dimension for the averaging, but this need not be the case. Lloyd„s algorithm starts by partitioning the input points into k initial sets, either at random or using some heuristic. It then calculates the average point, or centroids, of each set via some metric (usually averaging dimensions in Euclidean space). It constructs a new partition by associating each point with the closest centroids, usually using the Euclidean distance function. Then the centroids are

recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence, which is obtained when the points no longer switch clusters (or alternatively centroids are no longer changed.

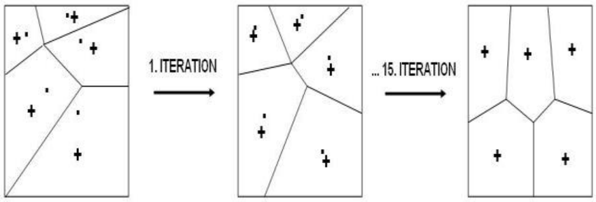


**Fig 2: Voroni Iteration**

## 2.2 Lloyd on Image

Let"s use the 8 bit Lena grayscale picture, dimensions 256×256 pixels. This gives us a total pixel number of 65536. Each of these pixels is in the 8 bit value range from 0 (black) to 255 (white). We can count how many pixels of each value there are, creating a histogram (probabilities over pixels). This is an important procedure that gives us information about the entropy and about the occurrence probability of each value. Lloyd„s algorithm will be adaptive to these characteristics. To generalize the procedure, the values can also be called symbols (each symbol represents a value). The histogram can be interpreted as a probability density function (PDF) which in our case is discrete. If we want to quantize an image using Lloyd and an M-level quantization, we have to divide the 27 Symbols (possible values) into M sets. The resulting partition is called initial set. The main objective of Lloyd„s algorithm is to minimize a distance metric within each set. Applied on images,

**Fig 3: Lena gray scale 256 x 256 x 8bits**

Lloyd minimizes the "distance" between the corresponding values of an interval to its borders (the thresholds) using a certain condition, e.g. minimize mean squared error if MSE is used as distance metric. With every iteration, the thresholds are moved as well (threshold condition) so that the partition changes from iteration to iteration, until a certain break condition is reached or there are no further changes. It„s also possible to apply specific constraints with additional conditions, an important example would be the entropy constrained scalar quantizer which changes the partition in order to reach a predefined entropy after quantization.
Note: the corresponding value of an interval will now be called its representative level. In this thesis, we use "basic" Lloyd algorithm which just minimizes the mean squared error in each interval.

## 2.3 Classified Vector Quantization

Initial studies of image coding with VQ have revealed several difficulties, most notably edge degradation and high computational complexity. People address these two problems and propose a new coding method, classified vector quantization (CVQ), which is based on a composite source model. Blocks with distinct perceptual features, such as edges, are generated from different sub sources, i.e., belong to different classes. In CVQ, a classifier determines the class for each block, and the block is then coded with a vector quantizer designed specifically for that class. They obtain better perceptual quality with significantly lower complexity with CVQ when compared to ordinary VQ.

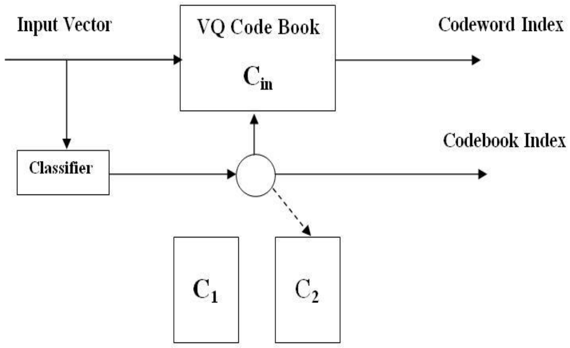


**Fig 4: Block diagram of Classified VQ**

## 2.4 Mean Removal Vector Quantization

To get around the unwanted blocky effect, associated with basic VQ, and the need to store a separate codebook for each image, Mean Removed VQ (MRVQ) can be employed. This method basically performs the function its title entails by removing and storing the mean of each training vector before performing VQ. By doing this the LBG algorithm is then forced to make matches based on the energy associated with the shape and texture of the blocks and not the overall luminance.

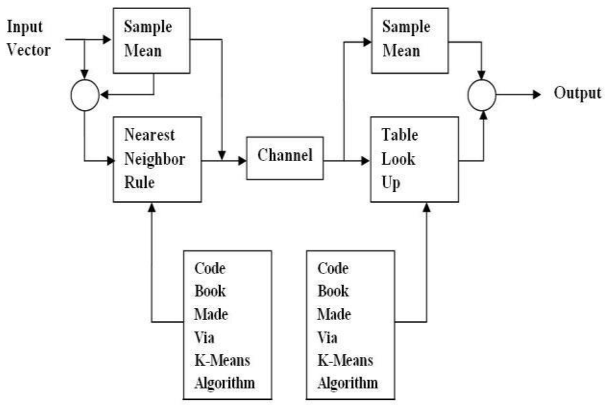


**Fig 5: Block diagram of Mean Removal VQ**

A universal codebook can now be created that enables the coder to make superior pattern matches as shapes and textures are more prone to be repeated over a wide variety of images when the mean is removed. A basic rundown on the mean removed VQ system can be seen in Figure.

## 2.5 Shape Gain Vector Quantization

Shape is the original image parameter whose image vector is normalized by the removal of the gain factor. Gain factor is the energy or variance of the codevector . Similar to other VQ techniques, image is divided into non overlapping blocks. Unit codevector is thereafter chosen to match with the image vector by maximizing the inner product over all codevectors in the shape codebook.

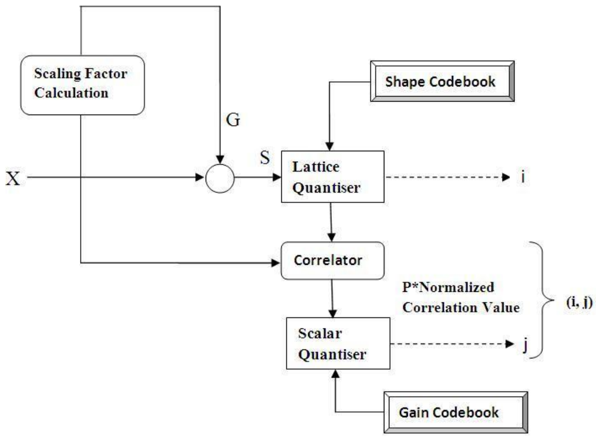


**Fig 6: Block diagram of Shape Gain VQ**

A shape vector „S", related to the orientation of x. The vector S is a scaled down version of x, forced to lie on the surface of a k-dimensional hyper sphere between the two inner most and outermost shells of the truncated lattice:

$$S = x \div G \qquad (3)$$

The scaling-down factor G is a set parameter of the encoder which depends only on the shells included in the shape codebook. The closest lattice point to the input shape vector y = L(S) is selected by the lattice nearest neighboring algorithm. To reconstruct the input vector x, the selected shape codevector y = L(S) is up scaled by the quantized value Q(G) of the gain factor. Thus the shape quantized vector is formed as the product of the quantized gain and the closest shape vector Y = Q(G)L(S). However, better results are obtained if, instead of scalar quantization of the gain G, normalized projection of the input vector x over the shape codevector y, P* is vector quantized. At a given orientation, the vector which always lies on the minimum distance from the input vector x is P, where its magnitude is the projection of x over y.

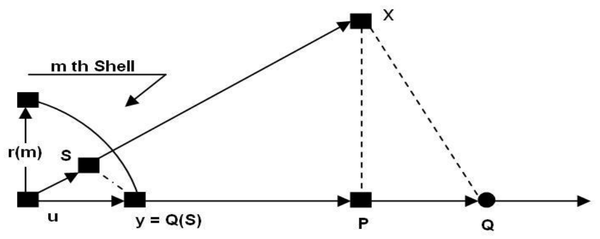


**Fig 7: Illustrate an analytical description of the Shape Gain quantizer**

Where in above figure:
x = input vector
S = x/G = scalar shape vector y = L(S) = shape code vector u = orientation of y
P = Pu = projection of x over y
G = GL(S)

# 3. RESULT

Table below shows the analytical results for signal to Noise Ratio (SNR) for different vector quantization techniques. Image of Lena grayscale 256x256x8bit is used for obtaining this result. As the dimension N x N is smaller the SNR is

**Table 1. Constrain analytical analysis for Signal to Noise Ratio (SNR)**

| Dimension N X N | Codebook Size | Signal to Noise Ratio (SNR) | | |
|---|---|---|---|---|
| | | **MRVQ** | **SGVQ** | **CVQ** |
| 2 | 32 | 14.9765 | 13.3426 | 14.9300 |
| 3 | 32 | 11.7324 | 10.0792 | 13.2956 |
| 4 | 32 | 09.7561 | 08.0879 | 17.4670 |
| 5 | 32 | 08.3600 | 07.1327 | 18.0590 |
| 6 | 32 | 07.5230 | 06.0581 | 15.7900 |
| 7 | 32 | 06.9473 | 05.2341 | 16.1000 |
| 4 | 8 | 05.3660 | 05.5578 | 14.7376 |
| 4 | 16 | 07.7890 | 06.9686 | 16.8166 |
| 4 | 32 | 09.7561 | 08.0879 | 16.4800 |
| 4 | 64 | 11.1684 | 09.2114 | 16.8425 |
| 4 | 128 | 11.9373 | 09.9600 | 19.5400 |
| 4 | 256 | 13.1165 | 10.9786 | 19.3600 |
| **Average SNR** | | **09.8691** | **08.3915** | **16.6182** |

comparatively high in Mean Remove VQ, for dimension 4 with codebook size 8 shows minimum SNR. In Shape Gain VQ the minimum SNR is obtained at dimension 7 with codebook size 32, whereas in Classified VQ technique minimum SNR is obtained at dimension 3 with codebook size 32. The SNR obtained using Classified VQ techniques are too higher than reaming techniques

# 4. CONCLUSION

From the above result we conclude that the Shape Gain Vector Quantization (SGVQ) is consistent in providing lowest SNR parameter and hence giving highest image quality during reconstruction at the decoder side.

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