# Image Vector Quantization Codec Indexes Filtering

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**Abstract.** Vector Quantisation (VQ) is an efficient coding algorithm that has been widely used in the field of video and image coding, due to its fast decoding efficiency. However, the indexes of VQ are sometimes lost because of signal interference during the transmission. In this paper, we propose an efficient estimation method to conceal and recover the lost indexes on the decoder side, to avoid re-transmitting the whole image again. If the image or video has the limitation of a period of validity, re-transmitting the data wastes the resources of time and network bandwidth. Therefore, using the originally received correct data to estimate and recover the lost data is efficient in time-constrained situations, such as network conferencing or mobile transmissions. In nature images, the pixels are correlated with their neighbours and VQ partitions the image into sub-blocks and quantises them to the indexes that are transmitted; the correlation between adjacent indexes is very strong.

There are two parts of the proposed method. The first is pre-processing and the second is an estimation process. In pre-processing, we modify the order of code-vectors in the VQ codebook to increase the correlation among the neighbouring vectors. We then use a special filtering method in the estimation process. Using conventional VQ to compress the Lena image and transmit it without any loss of index can achieve a PSNR of 30.429 dB on the decoder. The simulation results demonstrate that our method can estimate the indexes to achieve PSNR values of 29.084 and 28.327 dB when the loss rate is 0.5% and 1%, respectively.

**Keywords:** Vector quantization, Image communication, Index recovery, Filtering.

## 1 Introduction

The consumer electronic products are more and more popular nowadays. Digital camera and digital video become the essentials in daily life. Image processing is important because it is like a bridge between the natural scenes and users. When we catch an image from the camera, the image

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processing plays important role in many applications like image filtering, image compression, image scaling, etc. To meet the requirements of users, high-quality digital image processing tools are needed to fulfill the functionalities mentioned just now. Many papers have been developing to find better algorithms to solve it.

Many algorithms have already been proposed for image compression, because the size of natural images is huge so that it takes space to storage and time to transmission. In order to decrease image size, we use the data compression technique to reduce image data. Many image compression algorithms are proposed and devised.

Lossless compression is not needed in most of the applications. Lossy compression schemes can meet the requirement of real applications. Lossy encoding includes discrete cosine transform (DCT), block truncation coding (BTC), wavelet coding, vector quantization (VQ) coding, etc. In 1980, Gersho and Gray developed the vector quantization and many other researchers have been working on the research topic of VQ [1 – 7]. VQ is still one of the most successful signal processing techniques because it is quick and simple in decoding so that many applications that require fast decoding select this technique to compress data before transmission. Although this technique reduces image fidelity, it is still acceptable in many applications. Meanwhile having a high compression rate, the VQ method does not suffer from error propagation since it is a fixed-length source coding technique. The image VQ coding steps are shown in Fig. 1.

During encoding, it searches a best-matched code-vector in the codebook to replace input vector and transmit the index of the best-matched code-vector to the channel. On the decoder, using these received indexes to get code-vectors from the codebook and paste them to reconstruct the decoded image. The VQ can be viewed as a form of pattern recognition where an input pattern is ''approximated" by one of a predetermined set of standard patterns by matching it with one of a stored set of vector indexes in the codebook. We have always assumed that VQ indexes are transmitted to the receiver on noiseless channels and thus the receiver can reconstruct the image correctly. However, when the indexes are transmitted over a noisy channel, which is obviously most often the case, transmission errors usually occur. If the occurrence of transmission error, retransmission will be a good choice to reconstruct the image.

However, under the situation of time constraint, re-transmission takes time and increases the bandwidth so that it becomes another good choice if we can recover the image without retransmission. The transmission efficiency will be very poor if the transmission of VQ indexes occurs often over a noisy channel. Hence, some techniques have been explored to investigate the

transmission of VQ indexes over the noisy channels [8 – 13]. Essentially, one can take one of the two approaches to recover the lost indexes. We refer to them as VQ with prevention and VQ without prevention. In the first approach, VQ is trained for a noiseless channel and is sub-sequently made robust against channel errors by using an index assignment algorithm [11 – 13]. In the second approach [8-10], the noise detection and recovery is based on the idea that natural images usually have a high correlation between adjacent pixels. Some examples of VQ with prevention are pseudo-gray coding (PGC) [11] and anti-gray coding (AGC) [12]. Our method is based on the second approach.
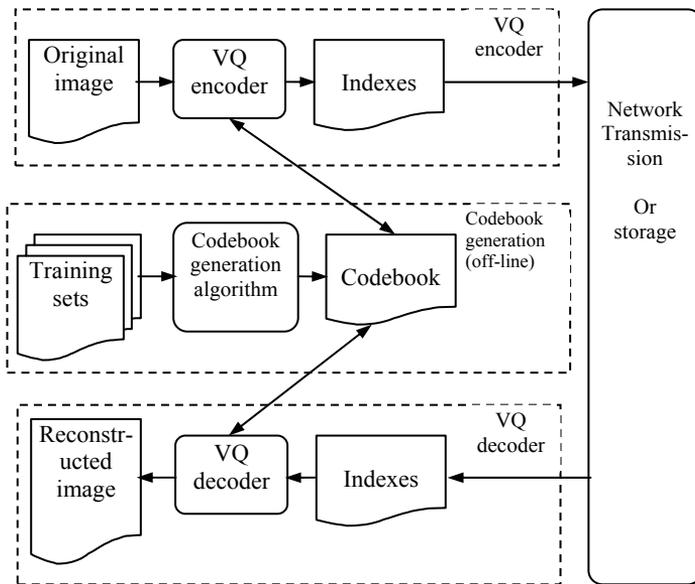


**Fig. 1 –** VQ *coding diagram*.

## 2   Vector Quantization Indexes Recovery

During the Internet transmission, random noises may cause the transmitting indexes to lose. The receiver can ask to re-transmit the indexes again. In order to save time, we proposed a method to estimate these lost data and to recover them instead of transmitting whole data again. Large data lost may cause the receiver to judge the occurrence of the network disconnection; therefore, the large data lost is monitored by the network rules. The main idea of our proposing method is decreasing the network traffic capacity while maintaining the quality as well as possible. In general, automatic recovery

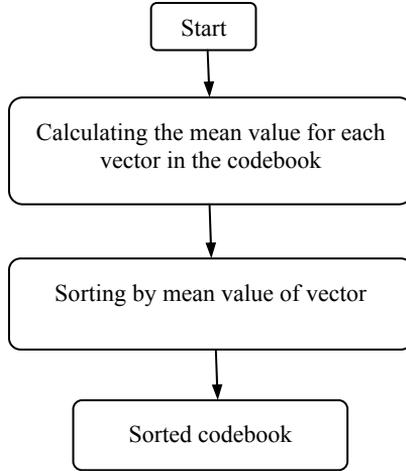will not be considered when the data is lost seriously, in which the system will re-transmit the data.



**Fig. 2 –** *Preprocessing diagram.*

The proposing method is efficient with respect to time constraint situation and bandwidth usage.

Fig. 2 shows the steps of the preprocessing. We use the mean value $m_i$ and the complexity to calculate the verification information. Notice that the codebook is global which means that we just yield it once and which can be used to encode all images. The preprocessing is yielded once as well.

We do not have to fulfill the preprocessing for every index recovery. In the conventional Linde, Buzo and Gray LBG codebook training processing, the code-vectors among the codebook do not have any special relationship. In the proposed method, the processed code-vectors among the codebook don't have the relationship of block mean and complexity. No methods of index estimation can guarantee the recovered index is the same as the index by full searching. Good estimation should get the index as close as possible to the best result. However, bias is unavoidable for all kind of estimation. Even thought the estimated index is not the best one, the mean difference between the predicted and best one is not huge so that the visual quality by the proposed method is acceptable.

The mean difference for nearby code-vectors is not huge; but the complexity could be different. Such a scenario will affect the visual quality seriously.

Various filtering techniques have been proposed for removing impulse noise in the past, and it is well-known that linear filters could produce serious image blurring.

As a result, nonlinear filters have been widely exploited due to their much improved filtering performance, in terms of impulse noise attenuation and edge/details preservation. One of the most popular and robust nonlinear filters is the standard median (SM) filter [14], which exploits the rank-order information of pixel intensities within a filtering window and replaces the center pixel with the median value. Due to its effectiveness in noise suppression and simplicity in implementation, various modifications of the SM filter have been introduced, such as the weighted median (WM) [15] filter and the center weighted median (CWM) [16] filter.

Conventional median filtering approaches apply the median operation to each pixel unconditionally, that is, without considering whether it is uncorrupted or corrupted. As a result, even the uncorrupted pixels are filtered, and this causes image quality degradation. An intuitive solution to overcome this problem is to implement an impulse-noise detection mechanism prior to filtering; hence, only those pixels identified as "corrupted" would undergo the filtering process, while those identified as "uncorrupted" would remain intact.

By incorporating such noise detection mechanism or "intelligence" into the median filtering framework, the so-called switching median filters [17] had shown significant performance improvement.

To solve this problem, a switching based adaptive median filtering scheme is proposed in this paper [18]. The new scheme is illustrated in Fig. 3. It exhibits improved performance in removing impulse noise while preserving fine details of the 2-D image (tow dimension) structure. In this algorithm, the filtering is applied to image indexes before image filtering.

The impulse detection is usually based on the following two assumptions: 1) a noise-free image consists of locally smoothly varying areas separated by edges, and 2) a noisy pixel has tendency of very high or very low gray value compare to its neighbors.
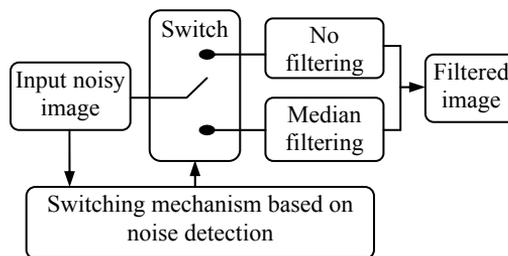


**Fig. 3** – *Block diagram of proposed filter*.

Two image sequences are generated during the impulse detection procedure. The first is a sequence of noisy indexes value, $x(i,j)$. $(i,j)$ is position of indexes, it can be $1 \leq i \leq M$, $1 \leq j \leq N$ where $M$ and $N$ are the number of the indexes in horizontal and vertical direction respectively, The second is a binary flag image sequence, $f(i,j)$ is used to indicate whether the received index at position $(i,j)$ detected as noisy or noise-free. If $f(i,j) = 0$ means index at position $(i,j)$ has been found as noise-free and if $f(i,j) = 1$ means index at position $(i,j)$ has been found as noisy.

*For noise detection:*

1. Lets take a $(2W+1) \times (2W+1)$ window around $x(i,j)$ means $x(i+k, j+l)$ where $-W \leq k \leq W$, $-W \leq l \leq W$ and $W \geq 1$.

2. Find Median value of this window $m(i,j)$

$$m(i,j) = \text{Median}[x(i+k, j+l)]; \qquad (1)$$

3. Find absolute difference between $x(i,j)$ and $m(i,j)$, and assign:

$$f(i,j) = \begin{cases} 0, & \text{if } |x(i,j) - m(i,j)| < T, \\ 1, & \text{otherwise,} \end{cases} \qquad (2)$$

$$T = \text{Median}\left(|x(i,j) - m(i,j)|\right), \quad 1 \leq i \leq M, \quad 1 \leq j \leq N,$$

where $T$ is predefined threshold value. "1" indicates that the index is detected as noisy.

4. If $(i,j)$ is detected as noisy then the value of $x(i,j)$ will be modified as:

$$x'(i,j) = \begin{cases} m(i,j), & \text{if } f(i,j) = 1, \\ x(i,j), & \text{otherwise.} \end{cases} \qquad (3)$$

## 3   Simulation Results

The quality measurement for reconstructed image is the Peak Signal to Noise Rate (PSNR):

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \quad [\text{dB}], \qquad (4)$$

where *MSE* is the mean square error between the original and the restored image.

We select the gray images including Lena, Goldhill, and Boat, whose size is 512×512 to be the test images. The codebook size is 256 and we select the threshold value $T = 60$ after repeating tests to classify the codebook as

described in the previous section. The selection of T influences the performance of the system. The value of Threshold is obtained by calculating the median value of variation of pixels relation (2). The codebook is created by LBG algorithm and the training images include Lena, Goldhill, and Boat. In the following experiments, all the images are encoded by the same codebook.

In order to show the performance, we compare the proposed method to other methods including the methods of [16, 17], tree median filter, the proposed filter applied to noisy indexes without filtering and the proposed method: proposed filter applied to received indexes before median filtering. **Table 1** lists two simulation results at different lost rates and the PSNR values of reconstructed image using different methods. Notice that, we all know that median filter can be used to eliminate the random noise. Therefore, we also use it for testing.

**Table 1**

*The quality of reconstructed image* (*Lena*) *expressed in* dB
*with different methods and different lost rates*.

| Lost rate(%) | 0 | 0.1 | 0.5 | 1 | 5 | 10 |
|---|---|---|---|---|---|---|
| Non recovery | 30.429 | 29.366 | 26.492 | 24.455 | 18.456 | 15.736 |
| 3 Median filter | 30.429 | 30.123 | 27.586 | 25.693 | 19.791 | 16.842 |
| Index filtering | 30.429 | 29.21 | 28.185 | 27.168 | 22.725 | 20.297 |
| Index filtering + median filtering | 30.429 | 29.801 | 29.084 | 28.327 | 24.228 | 21.718 |

**Table 2** shows the results to recover Goldhill and Boat by the different methods at the lost rate of 1%. By the observation of **Tables 1** and **2**, we can see that the proposed method for image recovery is efficient.

**Table 2**

*The quality of reconstructed images expressed in* dB
*with different methods at lost rates* 1%.

| Image | Boat | Goldhill |
|---|---|---|
| Non recovery | 23.962 | 24.106 |
| 3 Median filter | 24.863 | 25.461 |
| Index filtering | 25.015 | 26.736 |
| Index filtering+1 median filtering | 25.584 | 27.548 |

The importance of using the proposed method to image indexes at low data lost rates are not so obvious, but at high data lost rates (lost is in the edge blocks) the proposed method has the best results compared to all the other

methods. **Table 2** represent the result of proposed method for Boat and Goldhill images. The efficiency of our method is very obvious.

Now, we show the experimental results of codebook. Fig. 4 is the original Lena image whose size is 512×512. The codebook we used to encode Lena is created by LBG algorithm with the size of 256 code-vector. The bits to represent each index are eight. In fact, the Fig. 5 represents the collection of indexes after VQ encoding. It is like as the diminished image of Lena image from the observation of Fig. 5. Each pixel in Fig. 5 is the index for a 4 by 4 code-vector in the codebook so that the size of Fig. 5 is 128 by 128. We can see that the data in indexes map have a high correlation between adjacent pixels.



**Fig. 4** – *Original Lena image*.



**Fig. 5** – *Indexes map of Lena with codebook permutation*.



**Fig. 6** – *Indexes map at lost rate = 1%*.

**Fig. 7 –** *Recovered indexes map*.



**Fig. 8 –** *The* VQ *reconstructed Lena image*; PSNR = 30.429 dB.



(a)



(b)



(c)



(d)

**Fig. 9 –** (a) *Lost rate* 0.5% (*Lena*), PSNR = 26.492 dB;
(b) *Median filter at lost rate* 0.5%, PSNR = 27.586 dB;
(c) *Indexes filtering at lost rate* 0.5%, PSNR = 28.185 dB,
(d) *Proposed method at lost rate* 0.5%, PSNR = 29.084 dB.

(a)    (b)

(c)    (d)

**Fig. 10 –** (a) *Lost rate* 1% (Lena), PSNR = 24.455 dB;
(b) *Median filter at lost rate* 1% PSNR = 25.693 dB;
(c) *Indexes filtering at lost rate* 1%, PSNR = 27.168 dB;
(d) *Proposed method at lost rate* 1%, PSNR = 28.327 dB.

Fig. 6 is the indexes map at the lost rate of 1%. Fig. 7 is the indexes map reconstructed by the proposed method. Conventional VQ decoded Lena without any index lost is shown in Fig. 8 whose PSNR is 30.429 dB. Figs. 9a-9d and 10a-10d show the test images at different lost rates (0.5% and 1%). Fig. 9b shows the result at the lost rate of 1% by the median filter to reconstruct image.

Figs. 11-16 are the testing original images: Boat and ''Goldhill'', the VQ decoded images and the recovered images by the proposed method. Notice that the proposed code-book is the same as the one to encode Lenna, Boat and Goldhill.

Figs. 12 and 15 are the two images reconstructed by the conventional VQ decoder without any index lost. The lost rate is 1% for Figs. 13 and 16.

**Fig. 11 –** *Original Boat image.*



**Fig. 12 –** VQ *reconstructed Boat image*, PSNR = 28.832 dB.

**Fig. 13 –** *Recovered Boat image*, PSNR = 25.584 dB.



**Fig. 14 –** *Original Goldhill image*.

**Fig. 15 –** VQ *reconstructed Goldhill image*, PSNR = 29.413 dB.



**Fig. 16 –** *Recovered Goldhill image*, PSNR = 27.548 dB.

The PSNR degradation between the proposed method and without index lost is quite small. Our results show that the proposed method can achieve better results than the other methods. In addition, the recovery time of the proposed method is quite fast. This result shows our method could be used in time constraint applications. Our method facilitate the image recovery after index lost.

## 4   Conclusion

We present an efficient data recovery method for VQ encoded image transmission in this paper. During data transmission, if the data lost happens, we usually request the sender to transmit these data again. If the image or video has the limitation of the period of validity, re-transmitting the data wastes of time.

Hence, using the received correct data to estimate and recover the lost data is efficient in time-constraint situation. In our simulation result, using the received indexes to estimate the lost indexes to reconstruct image can yield good quality. The recovered image is almost indistinguishable to the original VQ decoded images. Therefore, these results show our method can efficiently improve the transmission quality when the time-constraint requirement is needed. The application of proposed method to the topic is successful. The method is suitable to noisy channels like mobile ones.

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