

## Re-quantization Codebook Using Fingerprint

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**Abstract:** Re-quantization is a key technology for reducing the bit rate of compressed data. The reduction of the bit rate and in certain cases may result in signal quality degradation. Techniques need to be deployed to enhance the signal quality based on optimization techniques. The proposed scheme constructed an optimal re-quantization codebook in an iterative manner for a given original quantization codebook that was constructed based on the quantization codebook of the transmitter. The construction process was iteratively repeated until a local optimum solution is reached. Algorithm implemented in fingerprint compression means using VQ codebook that had been computed from several previous training images. Better quality and low PSNR values were attained with this methodology compared with those using VQ codebook of several training images.

**Key word:** Vector quantization, LBG, fingerprint, re-quantization, compression

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### INTRODUCTION

The expansion in the fraudulent act in the last few decades has urged the world's governments to consider biometric as a measure for the control and monitoring of crimes and criminals. Fingerprint is one of those means. Fingerprints are becoming big business. The FBI started collecting fingerprints in the form of inked impressions on paper cards back in 1924 and today they have about 200 million cards, occupying an acre of filing cabinets in Washington, D.C. They also have many repeat customers, which is why only about 29 million out of the 200 million cards are distinct, these are the ones used for running background checks.) What's more, these cards keep accumulating at a rate of 30,000-50,000 new cards per day! Hence there is clearly an urgent need to digitize such collection, so that it occupies less space thus lends itself well to automatic search and classification.

However, the main problem is size (in bits). When a typical fingerprint card is scanned at 500 dpi, with eight bits/pixel, it results in about 10 Mb of data. Thus, the total size of the digitized collection would be more than 2000 terabytes, such amount of data is absolutely huge even by year 2008 standards. And this what stimulated the idea of this research as there is always a room for improvement even in the very modern technological methodologies<sup>[1,2]</sup>.

Re-quantization is an important technique for image communications over heterogeneous networks whose bandwidths are different. This technique gives a great result in the lack of flexible transmission through heterogeneous networks. The re-quantizer receives as an input a pre-quantized bit-stream with high bit rate to produce another bit-stream with lower bit rate that may meet the new bandwidth constraints<sup>[3]</sup>.

The re-quantization process has been considered and implemented in<sup>[4-7]</sup>. Bauschke *et al.*<sup>[4]</sup> proposed a heuristic re-quantization scheme for JPEG images. The Laplacian distribution model for AC DCT coefficients is used. In<sup>[5]</sup>, authors proposed another algorithm which is applied for re-quantization process for MP3 and MPEG-4 AAC, where an accuracy estimation algorithm for MP3 and AAC coding was proposed. However, no clear evidence is available that the re-quantization technique is better using on fingerprint with high accuracy analysis.

### MATERIALS AND METHODS

**Re-quantization the vector quantization:** Han and Kim<sup>[3]</sup> produced a re-quantization approach which works as follow; the  $X_i$  which is decoded with  $Q_1$  is quantized again with codebook  $Q_2$  (Fig. 1 shows a communication system using the re-quantizer over two channels). The second codebook is described as  $Q_2 =$

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$\{Y_0, Y_1, \dots, Y_{M-1}\}$ . Where the  $Q_2$  codebook size ( $M$ ) is smaller than  $Q_1$  codebook size ( $N$ ). The quantization using  $Q_2$  is represented as  $Y = Q_2(Q_1(V_1))$  where  $Q_2(Q_1(V_1))$  are not the same  $Q_2(V_1)$ .

In  $Q_1$ , the source vector  $V_1$  is mapped into the nearest codeword  $X_i$ . The selected  $X_i$  is compared with  $Y_j, j = 0, 1, \dots, M-1$  and the source vector  $V_1$  is quantized with  $Q_1$  and  $Q_2$  consecutively, the finally decoded codeword is  $Y_j$  in  $Q_2$ , while the  $V_1$  is directly quantized to  $Y_{j-1}$  with  $Q_2$  only. The discord can be represented as  $Q_2(Q_1(V_1))$ . We note that the final reconstructed signal  $X_i$  may differ from the  $Y_{j-1}$  due to the mismatch between the two codebooks. If we choose  $\{Y_j, j = 0, 1, \dots, M-1\}$  to reduce the distortion resulting from the mismatch, the re-quantization error can be diminished.

Let the transition probabilities  $P(Y_j|X_i), 0 \leq i \leq N-1$  and  $0 \leq j \leq M-1$ , denote the probability that the codevector  $Y_j$  is reconstructed, given that  $X_i$  is transmitted. Then the overall distortion is given by:

$$D(Q_1, Q_2) = \sum_{j=0}^{M-1} D_{Y_j} \tag{1}$$

where,  $Y_j$ :

$$Y_j = \frac{\sum_{i=0}^{N-1} P(Y_j|X_i) \sum_{l \in W_i} V_l}{\sum_{i=0}^{N-1} P(Y_j|X_i) \sum_{l \in W_i} \{1\}}, 0 \leq j \leq M-1 \tag{2}$$

Note that  $D(Q_1, Q_2)$  includes the distortions due to the quantization in  $Q_1$  and  $Q_2$ . The transition probability is:

$$P(Y_j|X_i) = \begin{cases} 1, & \text{if } X_i \in \{V_0, V_1, \dots, V_T\} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$D_{Y_j} = \sum_{i=0}^{N-1} \sum_{l \in W_i} P(Y_j|X_i) d(V_l, Y_j) \tag{4}$$

In optimization of  $Q_2$ , the codebook is designed by minimizing  $D_{Y_j}$  which minimizes  $D(Q_1, Q_2)$  for the fixed  $Q_1$ .

**Re-quantization algorithm:** The algorithm for re-quantization codebook is declared in the following steps<sup>[3]</sup>.

**Step 1: Design the initial codebooks  $Q_1$ :** The initial codebooks  $Q_1$  is made by LBG algorithm<sup>[1]</sup>. Where training vectors  $\{V_l, l = 0, 1, \dots, T-1\}$  are used and each vector  $V_l$  is generated by reading consecutive  $K$  pixel values from several training images.

**Step 2: Iter = 1,  $D^{(0)} = \infty$ :** The iteration number and the initial distortion are set to 1 and  $\infty$ , where  $\infty$  is implemented with a very large number in a practical system.

**Step 3: Design the codebook  $Q_2$  by using (2):** A new codebook  $Q_2$  is designed for a fixed  $Q_1$  by (2). Since Step 3 makes a set of new code vectors  $\{Y_j, j = 0, 1, \dots, M-1\}$ , the transition probability  $P(Y_j|X_i)$ , is changed although code vectors  $\{X_i, i = 0, 1, \dots, N-1\}$  are fixed.

**Step 4: Calculate  $P(Y_j|X_i), i = 0, 1, \dots, N-1, j = 0, 1, \dots, M-1$ :** The values of  $\{P(Y_j|X_i), i = 0, 1, \dots, N-1, j = 0, 1, \dots, M-1\}$  have to be calculated after construction of  $Q_2$ .

**Step 5: Calculate  $D(Q_1, Q_2)$ :** For codebooks  $Q_1$  and  $Q_2$  designed in Step 3, the overall distortion  $D$  is calculated.

**Step 6: If  $\{D^{(iter-1)} - D^{(iter)}\} / D^{(iter-1)} > \epsilon$ , then iter = iter+1 and go to step 3:** In this step the iterative design process will check the improvement of the system, where  $\epsilon$  is set to a very small number in practical implementation, for example, 0.001 or 0.0001.

**Step 7: Stop:** The algorithm stops when no significant improvement in  $D$  is achieved.

Hence, a successive application of Steps 3-5 results in a sequence of the codebook  $Q_2$  for which the corresponding  $D$ s form a strictly decreasing sequence of positive numbers, where a codebook  $Q_2$  is different from any one that the algorithm had generated previously. At the convergence stage,  $Q_2$  codebook with local minimal distortion is obtained. The optimization algorithm actually converges<sup>[3]</sup>.

## RESULTS AND DISCUSSION

In this study, we will compare the Re-quantization VQ with the tradition VQ algorithm in terms of Peak Signal to Noise Ratio (PSNR) and mean square error MSE.

Figure 1 and 2 shows the result of the reconstructed fingerprint images in PSNR (Fig. 2) and MSE (Fig. 3).

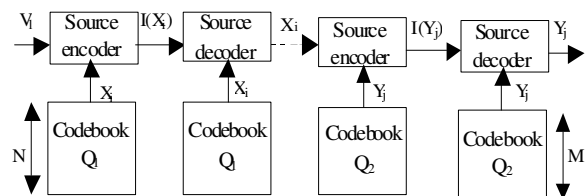


Fig. 1: Re-quantization Codebook<sup>[3]</sup>

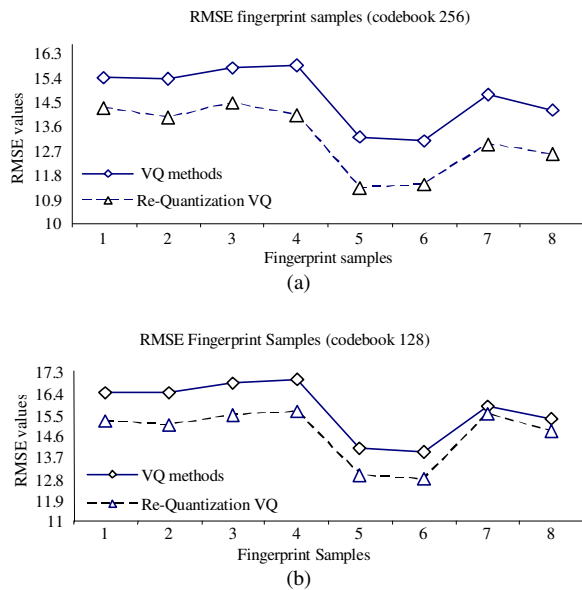


Fig. 2: RMSE fingerprint codebook compare between Re-quantization and VQ methods with (a-256 size b-128 size)

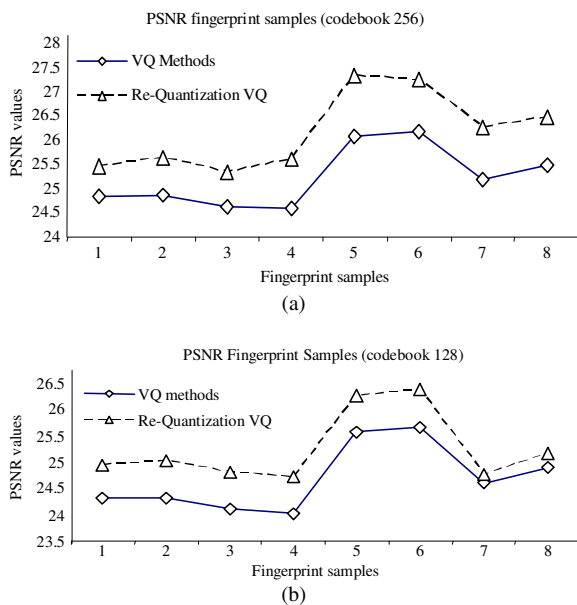


Fig. 3: PSNR fingerprint codebook compare between Re-quantization and VQ methods with a-256 size b-128 size

The performances are measured at various values of codebook size (128 and 256) the method been tested with 8 fingerprint samples different from the training samples. Fingerprint images samples have been chosen from<sup>[8]</sup> FVC2002 database.

Considering the efficiency of the compression algorithm, as a prime topic related to this article. The implementation considers the general Vector quantization idea in two ways: one uses the traditional VQ that is used the LBG algorithm and second the Optimal re-quantization, both these algorithms used the general codebook that is constructed from 40 different fingerprint images and been tested by differ fingerprint images that was not a part of the codebook. The two algorithms are tested on the fingerprint images samples. Figure 2 and 3 demonstrate that the techniques based on Optimal re-quantization exhibited higher PSNR comparing to the traditional VQ, with lower bit rates.

Also Optimal re-quantization keeps more texture information and improves visual quality of reconstructed images compared to the traditional VQ algorithm.

## CONCLUSION

We present the re-quantization and the conversional VQ methods for different fingerprint images. The general codebook that been prepared by 40 training images are tested with different 8 fingerprint sample images. Figure 2 and 3 gives the result of the re-quantization against the conversional VQ and we can infer that the Re-Quantization methods gives high PSNR and less MSR than the conversional VQ, even the compression ration for the Re-quantization methods are better than the conversional VQ.

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