Wavelet and Optimal Requantization Methodology for Lossy Fingerprint Compression

Zahraa Muhsen[1], Maher Dababneh[2], and Ayman Al Nsour[1]
[1]Faculty of Science and Information Technology, Isra Private University, Jordan
[2]University of Surrey London, UK

Abstract: *Re-quantization is a key technology for reducing the bit rate of compressed data. This reduction of the bit rate; and in certain cases may result in signal quality degradation. Therefore the proposed techniques used 9/7 wavelet transform before optimal re-quantization and finally, the output stream of coding symbols is entropy coded by lossless entropy coder; run-length encoding. Simulation results show that a better low Bit Rate has been obtained compared with other different techniques.*

Keywords: *Software engineering education, reflective learning and teaching, vector quantization, wavelet, 9/7 filter, general VQ, fingerprint, and optimal VQ.*

Received March 26, 2009; accepted November 5, 2009

1. Introduction

The common aim of different compression techniques is to achieve high compression ratio. But still there is a need to develop more efficient algorithms for image compression processing [6, 10, 11].

In general, image compression system can be designed of one or more of the following stages:

1. Transformation: a suitable transformation is applied to the image with the aim of converting it into a different domain where the compression will be easier. Another way of viewing this is via a change in the basic images composing the original. In the transform domain, correlation and entropy can be lower, and the energy can be concentrated in a small portion of the transformed image. Wavelet transformation is an effective method of compressing and de-noising the noisy signals, which proved very effective in the de-noising images.
2. Quantization: this is the stage that is mostly responsible for the 'lossy' character of the system. It entails a reduction in the number of bits used to represent the pixels of the transformed image (also called transform coefficients). Coefficients of low contribution to the total energy or the visual appearance of the image are coarsely quantized (represented with a small number of bits) or even discarded, whereas more significant coefficients are subjected to a finer quantization. Usually, the quantized values are represented via some indices to a set of quantizer levels (codebook). Optimal re-quantization improves the quality of the requantized image, an optimization scheme for the requantization codebook has been proposed by Han and Kim [5]. They proposed a scheme that constructs an optimal requantization codebook in an iterative manner for a given original quantization codebook of transmitter. The construction of codebook is iteratively repeated until a local optimum solution is reached. This approach can be applied not only to the scalar quantization, but also to any method which employs vector quantization-based system. The re-quantization process has been considered and implemented in [1, 2, 7, 12].
3. Entropy coding (lossless). Further compression is achieved with the aid of some entropy coding scheme where the nonuniform distribution of the symbols in the quantization result is exploited so as to assign fewer bits to the most likely symbols and more bits to unlikely ones. This results in a size reduction of the resulting bit-stream on the average. The conversion that takes place at this stage is lossless, in other words, it can be perfectly cancelled. The lossless entropy encoder RLE coder is used to prove this result.

Figure 1 shows the three major components of the image compression.

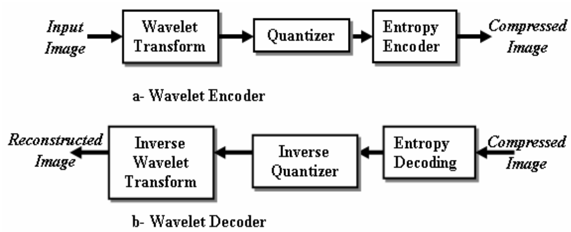

Figure 1. The structure of the wavelet transform based compression.

The 9/7 Wavelet filter bank decomposes an image into wavelet coefficients, which are then quantized by optimal re-quantization. Finally, an entropy encoder encodes these quantized coefficients into one bit stream i.e., compressed the image.

2. Wavelet for Compression

The theory of wavelet analysis has proved to be very important development in the search for more efficient methods of image compression. Wavelet transform can be used to analyze or decompose signals and images; thus decomposition process. Similarly, the same components can be assembled back into the original signal without loss of information thus; reconstruction or synthesis process and the same has been shown in Figure 2. The structure of the Wavelet can be represented as a four channel perfect reconstruction of filter bank. By using these filters in one stage an image can be decomposed into four bands. There are three types of images detail for each subsequent resolution: Diagonal (HH), Vertical (LH) and Horizontal (HL) [3, 4, 6].

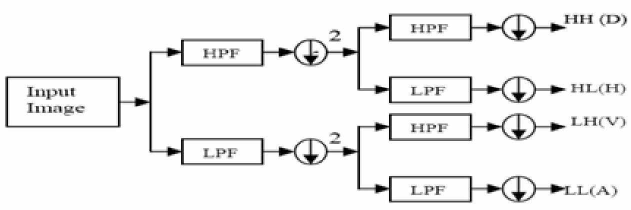

Figure 2. Wavelet structure- filter bank [9].

The decomposition process can be iterated, with successive approximations being decomposed. However, in practice, more than one decomposition level is performed on the image data. Successive iterations are performed on the low pass coefficients (approximation) from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original signal energy, this iteration process yields better energy compaction. However, the quality of the compressed image depends on the number of decomposition processes. Compression of an image can be obtained by ignoring all coefficients less than the threshold value. If decomposition iteration is used, better resolving Discrete Wavelet Transform (DWT) coefficient is obtained because Human Visual System (HVS) is less sensitive to the removal of smaller details [4].

3. Re-Quantization Algorithm

Figure 3 shows a communication system using requantizer over two consecutive heterogeneous channels whose transmission speeds are R_1 and R_2 respectively.

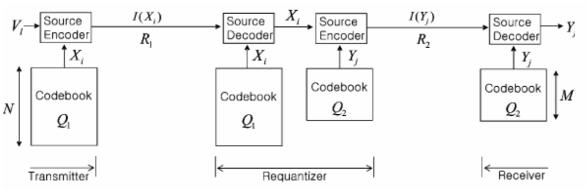

Figure 3. Communication system using re-quantization module [4].

In the re-quantization, the X_i which is decoded with Q_1 is quantized again with codebook Q_2. The second codebook is described as $Q_2= \{Y_0, Y_1, \ldots, Y_{M-1}\}$. Where; the Q_2 codebook size (M) is smaller than Q_1 codebook size (N). The quantization using Q_2 is represented as $Y=Q_2 (Q_1 (V_l))$ where $Q_2 (Q_1 (V_l))$ are not the same $Q_2(V_l)$ [5].

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

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

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

where Y_j is given as

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

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

$$D_{Y_j} = \sum_{i=0}^{N-1} \sum_{l \in W_i} P(Y_j \mid X_i d(V_l, Y_j) \quad (3)$$

$$P(Y_j \mid X_i) = \begin{cases} 1, & \text{if } X_i \in \{V_0, V_1, \ldots, V_T\} \\ 0, & \textit{otherwise} \end{cases} \quad (4)$$

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. The following steps explain the way to calculate the requantization codebook:

- Step 1 design the initial codebooks Q_1: the initial codebooks Q_1 is made using the LBG algorithm. Where training vectors $\{V_l, l=0, 1, \ldots, T-1\}$ 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 ∞ respectively, where ∞ is implemented with a very large number in a practical system.
- Step 3 design the codebook Q_2 by using equation 2: a new codebook Q_2 is designed for a fixed Q_1 by equation 2. Since Step 3 makes a set of new code vectors $\{Y_j, j = 0, 1, \ldots, M\text{-}1\}$, the transition probability $P(Y_j \mid X_i)$, is changed although code vectors $\{X_i, i=0,1,\ldots,N\text{-}1\}$ are fixed.
- Step 4 calculate $P(Y_j|X_i)$, i=0, 1, …, N-1, j=0, 1,…, M-1 the values of $\{P(Y_j|X_i), i=0, 1, \ldots, N\text{-}1, j=0, 1, \ldots, M\text{-}1\}$ 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 $\{D^{(\text{iter-1})}\text{-}D^{(\text{iter})}\}/D^{(\text{iter-1})} > \varepsilon$, then iter = iter+1 and goto step 3: in this step the iterative design process will check the improvement of the system, where ε 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 Ds form a strictly decreasing sequence of positive numbers, note through that the codebook Q_2 is different from any one that the algorithm had previously generated. At the convergence stage, Q_2 codebook with local minimal distortion is obtained. The optimization algorithm actually converges.

4. Result and Discussion

In this section the wavelet 9/7 filter and optimal requantization general VQ (WRGVQ) are compared with the wavelet 9/7 filter and the general LBG- VQ algorithm (WGLBG), it is also compared with wavelet 9/7 filter and the traditional general VQ (WGVQ) in terms of:

a. Peak Signal to Noise Ratio (PSNR).
b. Mean square error (RMSE).
c. Bit rate (BitR).
d. Compression ratio. These algorithms used more than 100 image samples for testing and training. The idea of general VQ been used for building the codebook for each methods.

To study the performance of these algorithms, the data from the FVC2002 [8] database have been considered. Tables 1, 2, 3, and 4 represent the corresponding average values for different number of training and testing fingerprint images. From these tables, it is clear that WGRVQ has the least BitR compared with WGLBG and WGVQ, and this is clearly shown in Figure 4.

The result of Tables 1, 2, and 3 are measured with PSNR, RMSE, and BitR at different sample of fingerprint images, these fingerprint samples differ from the training samples. In Table 1 the average values of each measures that have been taken from 5 training image and been tested by 7 fingerprint images Group 1. Table 2 on the other hand; use 20 training images with 40 test images Group 2. The average result of Table 2 has the highest result compared to that in Table 1. And finally Table 3 used 100 training fingerprint images and 80 test images Group 3, this shows that, the performance of (PSNR and RMSE) are lower than those in Table 2. This means that Table 3, which has the larger samples, has lower value results than those in Table 2. The result of (PSNR and RMSE) in all tables follows the Normal Distribution chart, and this can be clearly seen from Figures 5 and 6. Figure 7 shows sample images after using WGRVQ methods.

Table 1. Result of group 1 (5 training & 7 tested fingerprint).

Methods	Bitr	PSNR	RMSE
WGRVQ	0.2086	20.6123	24.818
WGLBG	0.3034	21.845	25.964
WGVQ	0.5774	21.909	26.255

Table 2. Result of group 2 (20 training & 40 tested fingerprint).

Methods	Bitr	PSNR	RMSE
WGRVQ	0.1570	24.1658	15.3989
WGLBG	0.1717	25.1711	14.1108
WGVQ	0.5666	25.1942	14.0479

Table 3. Result of group 3 (100 training & 80 tested fingerprint).

Methods	Bitr	PSNR	RMSE
WGRVQ	0.0689	19.1716	27.8006
WGLBG	0.0754	20.5731	23.6143
WGVQ	0.5291	15.0938	43.9012

Table 4. Result of compression ratio for group 3.

Methods	Compression ratio
WGRVQ	6:1
WGLBG	5:1
WGVQ	2:1

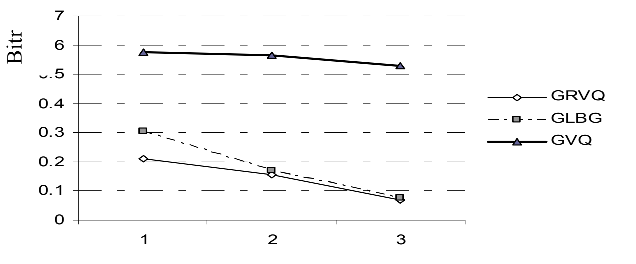

Figure 4. The average of the Bitr for each group, group 1, group 2, and group 3.

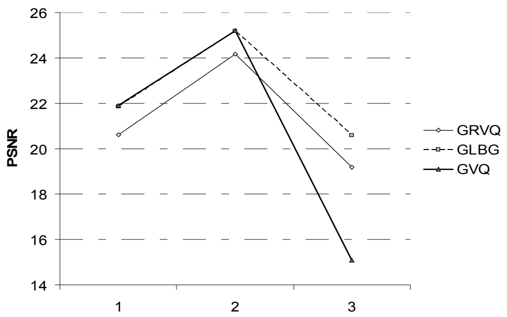

Figure 5. The average of the PSNR for each group, group 1, group 2 and group 3.

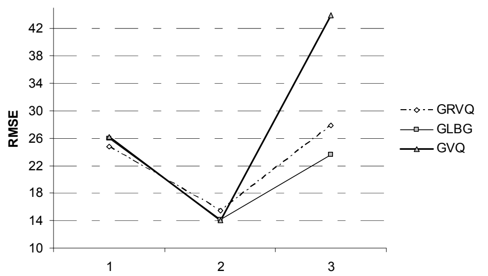

Figure 6. RMSE for three groups of training and testing fingerprint images, group 1, 2 and 3.

a- RMSE=29.9, PSNR=18.6, compR=5:1.

b- RMSE=31.7, PSNR=18, compR=4:1.

Figure 7. Image samples of using WGRVQ methods.

5. Conclusions

The Re-Quantization and the conventional VQ methods are presented in an image compression technique for different fingerprint images. The general codebook that had been prepared by different training images and been tested with different fingerprint sample images as shown in tables. Figures explain that the results are following the idea of normal distribution chart. This work gives the same result of the re-quantization against the conversional VQ as in [5], and it can be inferred that the Re-quantization methods gives less bit transmit than the conventional VQ even when using wavelet transform.

In our previous discussions, we have reported some remarks related to the behaviour and performance of the suggested methods, the following points improve the above works:

1. A large number of fingerprint image for building one codebook (General codebook), reduce the number of bit/ rate.
2. The wavelet of type 9/7 filter bank has a high compression ratio then other types, (used by JPEG2000).
3. The Requantization process has a high quality than the conventional VQ [5, 9].

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Zahraa Muhsen is an assistant professor at the Faculty of Science and Information Technology at Isra Private University, Jordan. She got her BSc and MSc in 1995 and 1998, respectively from the Computer Science Department, Mosul University, Iraq, and PhD in 2004 from the Technology University of Baghdad, Iraq. Before joining IPU, she worked as an assistant professor at Al Mansour University Baghdad, Iraq during the Period 1999-2005. Her research interests include image processing, artificial intelligence, mobile communication, and m-learning.

Maher Dababneh received his BSc and PhD degree in electrical engineering from Wales University, UK in 1989 and 1992, respectively. He worked as a postdoctoral senior research at the same university in 1993. In 1994, he joined the European LINK program in connection with DTI and AT&T as a project manager. He was the managing director of a network firm in Jordan 1995-1997. He is a member of the editorial board of the Jordan engineering journal. He is a technical committee member of a number of international Journals in IT. He is a lecturer at Isra Private University since 1995. He is a visiting professor for a 4 years term at Surrey University Guildford UK since September 2004. He is appointed the head of KADDB-Isra Bureau for research.

Ayman Al Nsour is an associate professor at the Faculty of Science and Information Technology at Isra Private University, Jordan. He got his PhD in 1995, from The University Keiv Polytechnical Institute. He spent one year sabbatical leave in UCF, USA. His research interest includes cryptography, information and computer network security, elearning, neural networks, and character recognition.