LOGARITHMIC QUANTIZATION INDEX MODULATION: A PERCEPTUALLY BETTER WAY TO EMBED DATA WITHIN A COVER SIGNAL

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ABSTRACT

In this paper, a new method for logarithmic Quantization Index Modulation (QIM) is proposed. In this regard a logarithmic function is first applied to the host signal. Then the transformed signal is quantized using uniform quantization as conventional QIM to embed watermark data within. Finally using inverse transform the watermarked signal is obtained. The watermark extraction is performed using minimum distance decoder. The optimum parameter for data embedding with minimum quantization distortion is derived. Also the probability of error is analytically calculated and verified by simulation. Furthermore data hiding using secret key is proposed and the probability of error is obtained. Simulation results show that the proposed method outperforms the conventional QIM in terms of robustness when the perceptual quality of watermarked image for both methods are similar. Moreover, simulation shows that the proposed scheme has outstanding robustness in comparison with a recent quantization based data hiding method.

Index Terms— QIM, logarithmic quantization, digital watermarking, Generalized Gaussian Distribution

1. INTRODUCTION

Among many watermarking schemes presented so far, the class of Quantization Index Modulation (QIM) methods proposed in [1] has grabbed the attention of researchers due to its good rate distortion-robustness tradeoffs. According to QIM, the watermark data is embedded by quantizing the host signal features using a set of quantizers, each of which associated with a different message. QIM is a blind method in which the original signal is not needed to extract the watermark data. Also, the embedding and extraction functions are simple and easy to implement.

The main problem of QIM is designing codebooks of the quantizers. Many previously proposed QIM-based data hiding methods used uniform quantization [2]. The uniform quantization is optimum when the host signal is uniformly distributed. For the hosts with non-uniform distributions, there exists a set of optimum quantizer levels, by the use of which, quantization introduces minimum distortion to the host signal. Furthermore, uniform quantization results in host-independent watermark signal. In this manner, the watermark signal can be easily estimated by averaging on a set of watermarked signals. Also, by uniform quantization, the perceptual characteristics of the host signal are not considered and the watermark power is distributed uniformly within the host signal, which introduces perceptible distortion in some parts of it. A quantization-based watermarking approach in the logarithmic domain has been proposed in [3] which features perceptual advantages. However, in [3], a simple logarithm function has been used for quantization. Thus, the quantization distortion cannot be controlled and minimized regarding the host signal distribution.

Unfortunately, obtaining optimum quantizer levels is rather hard in general. Furthermore, implementation of such a quantization scheme is difficult and needs an exhaustive search through quantization levels. In this paper, inspired by a standard usually used in the processing of speech signals called μ-Law [6], we propose a new method for logarithmic QIM and will call it LQIM throughout this text. Here, the host signal features are transformed using a logarithmic function and then quantized uniformly regarding the watermark data. The watermarked data is obtained by applying inverse transform to the quantized data. Minimum distance decoder is used to extract the watermark data. Also, the optimum μ which results in minimum quantization distortion is obtained analytically according to the host signal distribution. Using the proposed method, a host-dependent watermark will be obtained. Also, as a result of introducing host- dependent watermark, stronger watermark data can be inserted by LQIM in comparison with Uniform QIM (UQIM) with similar perceptual quality of watermarked data. The probability of error is derived for the proposed scheme by considering the host signal to follow Generalized Gaussian Distribution (GGD). The validity of analytical derivations is verified by simulation. Furthermore, data hiding using secret key is proposed and the probability of error in this case is also derived. Simulation results show the outstanding robustness of the proposed scheme in comparison with UQIM and another recent quantization-based algorithm.

2. LOGARITHMIC QUANTIZATION INDEX MODULATION

Inspired by the μ-Law concept, we propose a logarithmic quantization by which stronger watermark can be inserted that introduces less distortion to the host signal. The rational behind the logarithmic quantization is that since signal's amplitudes are more concentrated around zero, more step sizes should be devoted to quantizing smaller amplitudes and less should be associated to the larger amplitudes. This also leads to a more uniform signal-to-quantization error ratio for different amplitudes. In order to perform logarithmic quantization, the host signal must be transformed using the following compression function:

$$c = \frac{\ln(1 + \mu \frac{|x|}{X_{max}})}{\ln(1 + \mu)} \tag{1}$$

where μ is a parameter defining the compression level and X_{max} is the maximum value of the host signal features. These values should be known to the decoder. Since the maximum value in the host signal may be disorderly large, the maximum value should be defined regarding the probability density function (pdf) of the host signal. For example, we choose the maximum value in a way that the probability of larger values is 10^{-3}. It is worth mentioning that when μ tends toward infinity, the compression function can be proved to reduce to a simple logarithm function, leading to an approach similar to the one followed in [3]. The transformed signal is then used for data embedding. In this regard, the transformed signal is quantized uniformly regarding the watermark data similar to the UQIM [1]. The quantized data is then expanded, in order to obtain the watermarked signal, as follow:

$$y = \mathrm{sgn}(x)\frac{X_{max}}{\mu}[(1+\mu)^{z} - 1] \tag{2}$$

where $\mathrm{sgn}(\cdot)$ is the sign function and z is the quantized signal. In order to extract the watermark data, the minimum distance decoder is used. Minimum distance decoder can be implemented in the original domain or the transformed domain. We found, both analytically and experimentally, that the implementation in the original domain results in better robustness. The analytical calculation of the probability of error is discussed in Section 3.2. In this regard zero and one are embedded in the received signal (r) using the proposed method resulting in r_0 and r_1, respectively. The watermark data can be extracted by the following equation:

$$\hat{m} = \arg\min_{i\in\{0,1\}} \|r - r_i\|^2 \tag{3}$$

where $\hat{m}$ is the extracted watermark data. Decoder needs μ, X_{max} and quantization step size to extract the watermark data. Other decoders such as Maximum Likelihood decoder can also be used to extract data, but here we want to propose a simple one.

3. ANALYSIS OF THE PROPOSED METHOD

3.1. Optimum parameter finding

In order to obtain the optimum value for μ, we should find the watermark power and then minimize it with respect to μ. Consider the quantization noise to be w. Thus we have $z = c + w$. For obtaining the watermark power, we need to find $\mathrm{E}[\|y - x\|^2]$. Replacing z by $c + w$ in (2) we get:

$$y - x = \mathrm{sgn}(x)\frac{X_{max}}{\mu}[(1+\mu)^{c+w} - 1] - x, \tag{4}$$

$$y - x = x(1+\mu)^{w} + \mathrm{sgn}(x)\frac{X_{max}}{\mu}[(1+\mu)^{w} - 1] - x. \tag{5}$$

Simplifying the above equation leads to:

$$y - x = (x + \mathrm{sgn}(x)\frac{X_{max}}{\mu})((1+\mu)^{w} - 1). \tag{6}$$

From the above equation, $\mathrm{E}[\|y - x\|^2]$ can be found as

$$\mathrm{E}[\|y - x\|^2] = \mathrm{E}[(x + \mathrm{sgn}(x)\frac{X_{max}}{\mu})^2]\mathrm{E}[((1+\mu)^{w} - 1)^2]. \tag{7}$$

In (7) two terms inside the expectations have been considered to be independent and were found experimentally through scatter plots. For the first term we have:

$$\mathrm{E}[(x + \mathrm{sign}(x)\frac{X_{max}}{\mu})^2] = \sigma_x^2 + 2\mathrm{E}[|x|]\frac{X_{max}}{\mu} + \frac{X_{max}^2}{\mu^2},$$

where σ_x^2 is the host signal variance and the mean is assumed to be zero. According to the Bennett's high-rate model for quantization noise, quantization noise, w, is considered to follow uniform distribution between $[-\Delta/2, \Delta/2]$, where Δ is the quantization step size. Therefore we have:

$$\mathrm{E}[((1+\mu)^{w} - 1)^2] = \frac{1}{\Delta}\int_{-\Delta/2}^{\Delta/2}((1+\mu)^{w} - 1)^2 dw.$$

Here, in order to save space, we have written the compact form rather than its closed form. By replacing the resultant expectations into equation (7), the watermark power is obtained. The optimum value for μ will be obtained by finding the derivative of the watermark power with respect to μ and equating the result to zero which can be found numerically.

According to the obtained watermark power, Document to Watermark Ratio (DWR) can be calculated as:

$$\mathrm{DWR} = \frac{\mathrm{E}[\|x\|^2]}{\mathrm{E}[\|y - x\|^2]} = ((1 + \frac{X_{max}^2}{\sigma_x^2\mu^2}) \times (\frac{1}{\Delta}\int_{-\Delta/2}^{\Delta/2}((1+\mu)^{w} - 1)^2 dw))^{-1}. \tag{8}$$

As seen, when μ become large, the term $X_{max}^2/\sigma_x^2\mu^2$ can be neglected with respect to 1 and thus DWR will be independent of the host signal variance which leads to a watermark power proportional to the host signal power, similar to [3]. This is the major advantage of the logarithmic quantization over uniform quantization in which the DWR strongly depends on the host signal power.

3.2. Derivation of bit error probability

In this section the probability of error for the proposed scheme is calculated. We conduct the analysis by considering the watermarked signal to be sent through an Additive White Gaussian Noise (AWGN) channel. For the sake of generality, the original signal is modeled by a Generalized Gaussian Distribution (GGD) defined as:

$$f_x(x; \mu, \sigma, \nu) = \frac{1}{2\Gamma(1+\frac{1}{\nu})A(\nu,\sigma)} e^{-|\frac{x-\mu}{A(\nu,\sigma)}|^{\nu}} \tag{9}$$

where μ is the mean of the distribution, which we considered to be zero, σ is the standard deviation, ν is the shape parameter which describes the exponential rate of decay, $\Gamma(\cdot)$ is the gamma function and $A(\nu, \sigma)$ is defined as follows:

$$A(\nu, \sigma) = \sqrt{\frac{\sigma^2\Gamma(1/\nu)}{\Gamma(3/\nu)}}.$$

When $\nu = 1$, the GGD corresponds to a Laplacian distribution and if $\nu = 2$ it corresponds to a Gaussian distribution. The shape parameter (ν) is estimated using the method of moments, as follows [4]:

$$\nu = F^{-1}(\xi), \quad \xi = \frac{\mathrm{E}(|x|)}{\sqrt{\mathrm{E}(x^2)}}$$
$$F(\xi) = \frac{\Gamma(2/\xi)}{\sqrt{\Gamma(1/\xi)\Gamma(3/\xi)}}. \tag{10}$$

The probability of error can be obtained as follows:

$$P_e = \sum_{i=-\infty}^{\infty} o_i \sum_{m=-\infty}^{\infty} \int_{T_{i+2m}}^{T_{i+1+2m}} \frac{1}{\sqrt{2\pi}\sigma_n} \mathrm{e}^{\frac{(n-C_{i/2})^2}{2\sigma_n^2}} dn \quad (11)$$

where σ_n^2 is the noise variance, o_i is the probability of occurrence of the host signal in the interval $[C_{(i-1)/2}, C_{(i+1)/2}]$, which by assuming equal probabilities for zero and one bits, is defined as:

$$o_i = \frac{1}{2} \int_{C_{(i-1)/2}}^{C_{(i+1)/2}} \frac{1}{2\Gamma(1+\frac{1}{\nu})A(\nu,\sigma)} e^{-|\frac{x}{A(\nu,\sigma)}|^{\nu}} dx, \quad (12)$$

where C_i is:

$$C_i = \mathrm{sgn}(i) \frac{X_{max}}{\mu} [(1+\mu)^{(|i\Delta|)} - 1],$$

and T_i is defined as:

$$T_i = \frac{C_{i/2} + C_{(i+1)/2}}{2}.$$

4. DATA HIDING WITH SECRET KEY

In order to make the proposed method secure, we need to use a secret key for data hiding. In this regard, μ can be selected randomly around its optimum value. These values will be sent to the receiver side as a secret key to be used to extract data. In this manner, an attacker cannot find the quantization pattern due to the random location of quantization levels. The size of interval of these values around the optimum value depends on the level of security a system desires. Large interval results in a more secure system and consequently more deviation from the minimum distortion that data embedding with the optimum value introduces to the host signal. DWR of the watermarked data, in this case, can be obtained as:

$$\mathrm{DWR} = \int_{\mu_o - d_1}^{\mu_o + d_2} \frac{f_\mu(\mu)}{(1+\frac{X_{max}^2}{\sigma_x^2 \mu^2})\frac{1}{\Delta}\int_{-\Delta/2}^{\Delta/2}((1+\mu)^w - 1)^2 dw} d\mu, \quad (13)$$

where $f_\mu(\mu)$ is the distribution of μ, and μ_o is the optimum μ. As seen in this equation, the interval around μ_o can be asymmetric. Also the probability of error in this case is:

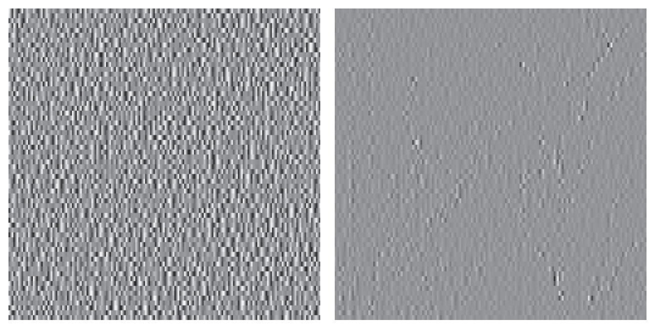
$$P_e = \int_{\mu_o - d_1}^{\mu_o + d_2} f_\mu(\mu) (\sum_{i=-\infty}^{\infty} o_i \sum_{m=-\infty}^{\infty} \int_{T_{i+2m}}^{T_{i+1+2m}} \frac{1}{\sqrt{2\pi}\sigma_n} \mathrm{e}^{\frac{(n-C_{i/2})^2}{2\sigma_n^2}} dn) d\mu \quad (14)$$

5. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed method, we tested LQIM on different well-known 512×512 images including Lena, Pepper, Baboon, Barbara, F16, etc. However, in order to save the space we bring the results only for Lena image. The results for other images were similar. Also, in order to show the advantage of LQIM, the results are compared with UQIM. In this regard, DCT coefficients for each 8×8 block were calculated. Data was embedded in the AC coefficient of each block located in the first row and second column. We used AC coefficients since they have stronger components in the complex part of the image which is more appropriate for our purpose. The quantization step size for uniform QIM was 22 and Δ for LQIM was selected equal to 0.11. These values were selected in order to have a similar perceptual quality for the watermarked image. Since the watermarked images for both methods were so similar that it was very difficult to recognize their differences perceptually, we used Watson distance [8] as a metric to evaluate the quality of watermarked images. The Watson distance for both methods were about 120. The optimum μ was found equal to 8.4 using the method described in section 3.1.

(a) (b)

Fig. 1. Watermarked Lena image (a) using UQIM and (b) using LQIM.



(a) (b)

Fig. 2. Scaled differences of the original and watermarked Lena images using (a) UQIM (b) LQIM.

The watermarked Lena images are depicted in Fig. 1 for both UQIM and LQIM. As can be seen, the quality for both methods is acceptable. Although the PSNR of the watermarked image for UQIM is 50 dB and for LQIM is 45 dB, their Watson distances and perceptual qualities are similar. The differences of the original and watermarked images in a magnified form are shown for both methods in Fig. 2. In this regard, we scaled the difference into range 0 to 255. As seen, LQIM provides image-dependent watermark which has strong components in the complex part of the image, which is hard to see. This allows us to insert strong watermark whereas the perceptual quality of the watermarked image is kept at acceptable level, while uniform QIM embeds data uniformly in the whole im-

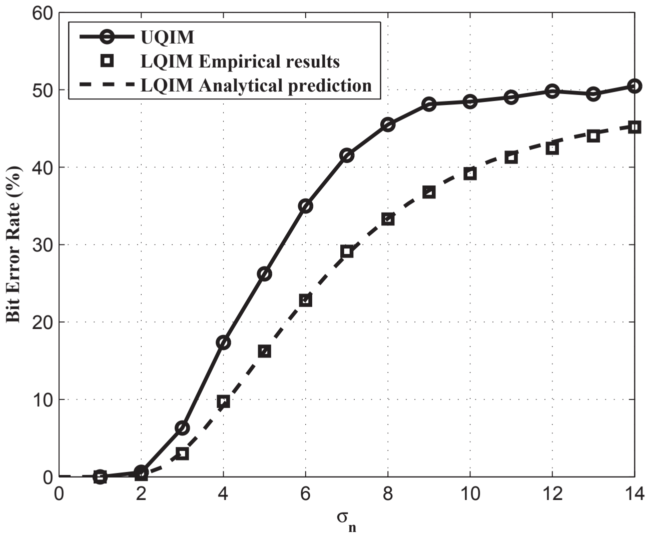


Fig. 3. BER(%) vs. SNR for AWGN attack. 4096 bits have been embedded in Lena image in both methods.

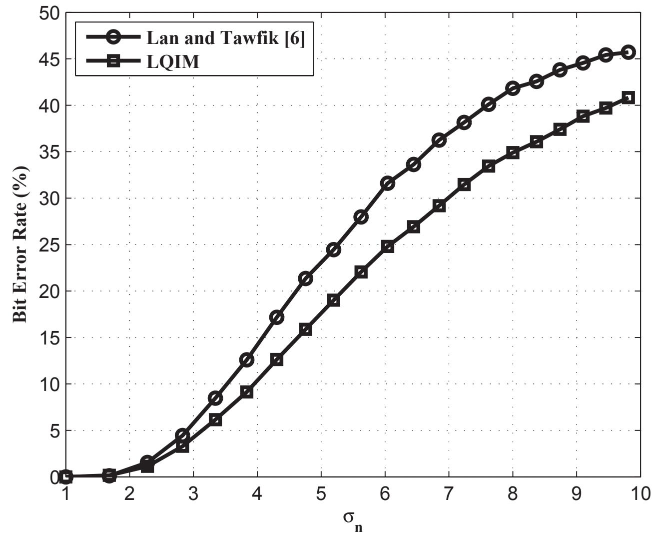


Fig. 4. BER(%) vs. SNR for AWGN attack. 12288 bits has been embedded within Lena image in both methods.

age, that can be seen easily in the less textured part of the image.

Fig. 3 demonstrates the robustness of the LQIM in comparison with UQIM under AWGN attack. As can be seen, LQIM, as a result of inserting a stronger watermark, outperforms UQIM. Also, the analytical prediction and empirical results are very close which shows that GGD models the DCT coefficients well. However, similar to UQIM, this method suffers from amplifying attacks, which can be alleviated with Rational Dither Modulation (RDM) [5]. In RDM, due to varying step sizes, the peak of distortion may be momentarily large which results in a perceptual impact on the host signal. Using LQIM, and by selecting a proper μ, this problem can be somewhat solved. Nonetheless, derivation of such value for μ was beyond the scope of this paper.

Also, the proposed method was compared with a quantization-based method proposed in [7] and the results are shown in Fig. 4. In both methods, the three first components in the first row of the DCT coefficients, including DC and two AC coefficients, were used for data embedding. The PSNR of [7] for Lena image was 45 dB and that of LQIM was 41 dB. Furthermore, the Watson distance for [7] was 210 and for our method was 170 which shows the better perceptual quality of our method. As seen, although the quality of our watermarked image was better than [7], our method shows a better robustness.

6. CONCLUSION

In this paper, a novel quantizer arrangement for quantization-based data hiding, called LQIM, was proposed. In this regard, we used a technique similar to the μ-law standard to transform the host signal and quantize the data in the transformed domain. Optimum μ was also found which results in introducing minimum distortion to the host signal. Using this scheme, stronger watermark can be inserted in the host signal in comparison with UQIM with the same quality of watermarked data. Also, data hiding using secret key was proposed which is similar to the dithering in UQIM. Simulation shows that this method outperforms UQIM as well as a recent quantization-based data hiding approach in terms of robustness and perceptual quality of the watermarked data.

7. REFERENCES

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