NON-UNIFORM QUANTIZER DESIGN FOR IMAGE DATA HIDING

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ABSTRACT

Most quantizer based data hiding schemes use uniform quantizer, which is not optimal if the host signal is not uniformly distributed. In this paper, we design a quantizer that is not only *pdf*-matched but also more suited to embedding than the Linde-Buzo-Gray (Lloyd-Max) algorithm for vector (scalar) quantizer design. Experimental results shows that the proposed scheme provides better trade-offs between robustness to attacks, embedding induced distortion and embedding capacity than a simple *pdf*-matched scheme. The proposed algorithm also shows about 3dB improvements in embedding distortion over other popular quantizer based embedding algorithms.

1. INTRODUCTION

Data hiding has become increasingly important in a variety of applications, one of which is security. Several aspects of data hiding have been explored by researchers, including theoretical analysis of the information hiding capacity [1, 2, 3]. The existing data hiding methods can be classified into quantization based [4, 5, 6, 7], spread spectrum based [8, 9], bit replacement based [10] and prediction based schemes [11, 12]. All quantization based schemes can be traced back to Costa's work [13], where he proposed a special communication scheme with side information, achieving the theoretical capacity of the standard Gaussian channel. Since the ideal Costa scheme (ICS) can be considered as a data hiding scheme under additive white Gaussian noise (AWGN) attacks, the capacity achieved by ICS becomes the upper bound for all data hiding schemes in the presence of such attacks. However, the ICS is not practical because of the huge size of its random codebook [5]. Practical quantization based schemes that implement Costa's idea include Quantization Index Modulation (QIM) [4], Scalar Costa Scheme (SCS) [5] and Quantization Projection (QP) [14].

All these schemes are based on uniform quantizers, which is optimal only if the host signal is uniformly distributed. In our previous work [15], we proposed a *pdf*-matched scheme for embedding in images, in which, the embedding algorithm was based on the Linde-Buzo-Gray (LBG) vector quantizer (VQ) [16]. We showed that this scheme performs better than uniform quantizer based schemes [15]. Although the LBG VQ is *pdf*-optimal (for quantization per se), our *embedding* scheme can be further improved if we adopt a quantizer which is not only matched to the *pdf* of the host signal, but which also provides a better trade-off between the three important parameters in data hiding, namely, embedding distortion, embedding capacity and robustness to attacks. In this paper, we propose a new *pdf*-matched scheme by searching for suitable embedding regions.

2. *PDF*-MATCHED QUANTIZER BASED EMBEDDING

Fig. 1 shows the structure of the *pdf*-matched embedding (PME) scheme discussed in [15]. In this scheme, a vector quantizer is first designed using, say, the Linde-Buzo-Gray (LBG) algorithm. The vector quantizer design algorithm partitions the host signal space into Voronoi regions. A *subset* (rather than the whole) of each Voronoi region is selected as the embedding region and is denoted by squares in the figure. Host image vectors falling in these regions are used to embed the hidden data. For example, in the 2-D case, the host image is taken as 2-D vectors and *2-D bit vectors are embedded in each region.* Each bit vector is associated with a perturbation vector. The image vector in the embedding region (E_i) is replaced by the perturbed vector ($\vec{p}_j$) corresponding to the bit vector to be embedded in the region. The amount of perturbation determines the robustness of the embedding algorithm

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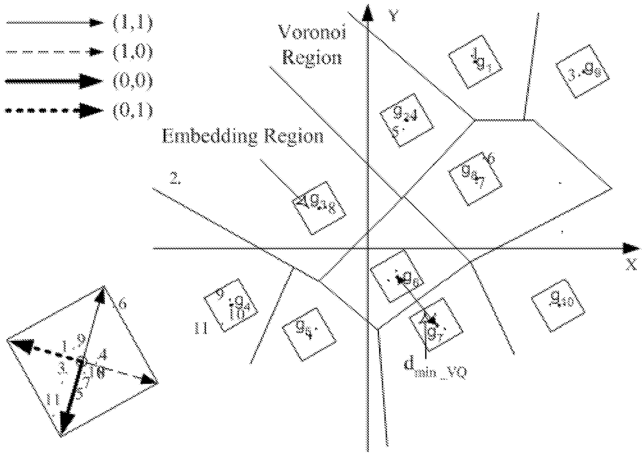

Fig. 1. The 2-D PME Scheme

to additive noise. If D_w denotes the average distortion due to embedding and $d_{\min}$ denotes the minimum distance between the cosets induced by the embedded vectors, then the parameter $d^2_{\min-\text{norm}}$ is defined as:

$$d^2_{\min-\text{norm}} \equiv \frac{d^2_{\min}}{D_w}. \tag{1}$$

and captures the robustness versus distortion trade-off.

2.1. Need for Special Non-Uniform Quantizer Design Algorithm

Although the LBG algorithm is *pdf*-matched to the host image, it is not specifically optimized for data embedding. This is because, a generic *pdf*-matched quantizer design algorithm minimizes the average distortion due to quantization and not due to embedding. If $\vec{g}_i$ represents the centroid of the i^{th} Voronoi region V_i and $\vec{x}$ denotes the host image vector, the average distortion of the VQ is given by D_C:

$$D_C = \sum_i \int_{V_i} \|\vec{x} - \vec{g}_i\|^2 f_X(\vec{x}) d\vec{x}, \tag{2}$$

while the average distortion caused by embedding is given by D_E:

$$D_E = \sum_i \int_{E_i} \sum_j \|\vec{x} - \vec{p}_j\|^2 \Pr(\vec{p}_j) f_X(\vec{x}) d\vec{x}. \tag{3}$$

Since $D_E \neq D_C$ in general, a generic vector quantizer (non-uniform scalar quantizer) design algorithm is not optimal for embedding applications. In the next section we present a simple algorithm that searches for the best embedding region for the scalar embedding case.

3. THE PROPOSED NON-UNIFORM QUANTIZER DESIGN ALGORITHM

Let $d_{\min}$ be the size of the embedding region. Let $\mathcal{R}_i$ be the search region for the i^{th} iteration of the algorithm. Let R be the range of the signal (0 to 255 for images). Select a threshold value T_h for the $d^2_{\min-\text{norm}}$ (as in Equation 1). This value determines the robustness of the embedding algorithm and will determine the number of codewords in the quantizer. Set μ as the displacement unit for the search algorithm. Then the algorithm is given by:

```
    Set R_0 = R, Set i = 0;
*:  Slide embedding region in steps of μ along
      the all of R_i from the left to right, and
      calculate d²_min−norm for each displacement;
    Find max value of d²_min−norm: max_i(d²_min−norm);
    If max_{R_i}(d²_min−norm) < T_h
        STOP;
    else Set the corresponding embedding region
          as the i^th embedding region E_i.
        R_i ⟵ R_i − E_i;
        i++;
        Goto *;
    end
```

Note: For applications where more than one host image is used to embed different messages, a training set of images can be used to design a general non-uniform quantizer that can then be used for an entire class of host images.

4. EXPERIMENTAL RESULTS

We used the 512x512 Barbara image as the host and a random bit sequence with $P_r(0) = P_r(1) = \frac{1}{2}$, was embedded. The number of bits embedded depends on the capacity of the scheme. We test the performance of our scheme (which we denote as ERSS) with QIM and the PME scheme proposed in [15]. In [4] Chen and Wornell proposed a distortion compensation (DC) technique, where, the compensated stego-signal (S) is equal to the sum of the stego-signal (Xq) and a compensation parameter, which is a scaled version of the watermark signal (X - Xq):

$$S = X_q + (1 - \alpha)(X - X_q) \tag{4}$$

Here the scaling factor (α) depends on the average distortion due to embedding (D_w) and the variance, σ_n^2, of the AWGN attack:

$$\alpha = \frac{D_w}{D_w + \sigma_n^2} \tag{5}$$

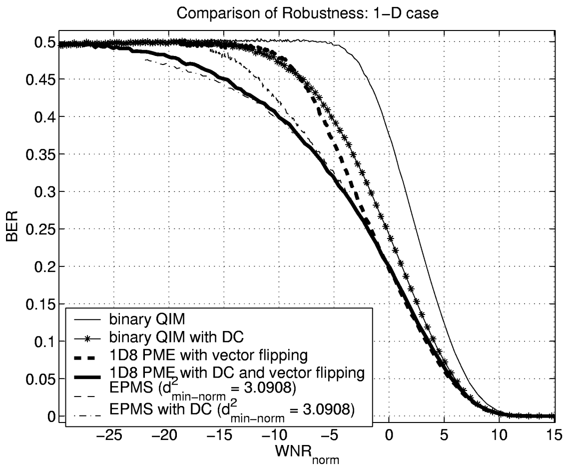

Fig. 2. Comparison of robustness between QIM, DC-QIM, VF-PME, DC-VF-PME, ERSS, and DC-ERSS (1-D case)

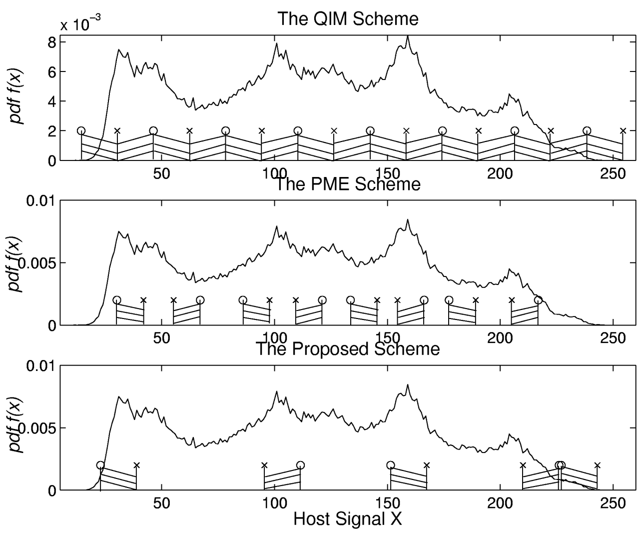

Fig. 3. Comparison of embedding regions in the QIM, PME and the proposed scheme. x: the coset for hidden bit '1'; o: the coset for hidden bit '0'; Y axis: *pdf* of Barbara image. Shaded area is embedding region.

Scheme	$d_{\min}$	R_m	α	VF	$d^2_{\min-\text{norm}}$
QIM	16	1	N/A	N/A	2.9969
PME	10.40	0.423	0.25	N	2.9931
	20.81	0.846	0.5	Y	3.0204
	11.78	0.475	0.283*	Y	3.0206*
ERSS	16	0.658	N/A	Y	3.0613
	16	0.343	N/A	Y	3.0908

Table 1. Embedding Rate for 1-D QIM, PME and ERSS (* denotes optimal value)

We also extend our current scheme using the same technique and compare it with the distortion compensated versions of QIM and PME. Finally, we note that reversing the perturbation vector corresponding to a '0' and '1' improves the robustness of the scheme further. We also present comparisons of this vector flipped (VF) version of all algorithms here.

Figure 2 compares the performance of the ERSS and DC-ERSS against that of the *pdf*-matched scheme with vector flipping [15] (VF-PME), DC-VF-PME, QIM and DC-QIM in terms of the probability of bit error under AWGN attacks. We base the robustness comparison on the normalized watermark distortion to noise ratio ($\text{WNR}_{\text{norm}} = \frac{D_w}{\sigma_n^2 * R_m}$) in order to ensure a fair comparison between our schemes and these. The results of our comparison in the 1-D case are presented as bit error rate (BER) versus WNR_{norm} plots in this Figure. It can be seen that the binary QIM performs worst in all the three sets of experiments, as expected. On the other hand, the best performing algorithm is DC-ERSS.

In Figure 3, we plot the *pdf* of the host image (512x512 Barbara) and mark the embedding regions for the QIM, PME and the ERSS schemes. As can be seen from the figure, the QIM scheme uses all of the image to embed, but the embedding regions are not matched to the image *pdf*. In the PME scheme using the Lloyd-Max algorithm, the embedding regions are better matched to the *pdf*, but comparing this to the embedding regions in the proposed scheme shows that the proposed scheme has the best embedding regions, since they are centered around the peak regions in the *pdf*. Finally, Table 1 shows the embedding rates R_m and $d^2_{\min-\text{norm}}$ for all three schemes. As can be seen from this table, the proposed scheme has comparatively higher values of $d^2_{\min-\text{norm}}$ implying that it is more robust to additive noise attacks.

5. CONCLUSION

This paper showed that using a generic *pdf*-matched quantizer design algorithm is not optimal for data-hiding application. We then proposed a non-uniform quantizer design algorithm for data-hiding in images which essentially searches for the best regions to place the embedding region within the image range. The proposed algorithm shows better performance in terms of embedding rate-embedding distortion-robustness trade-offs than a scheme using the Lloyd-Max quantizers, and QIM. We note that although we showed examples of data hiding in the spatial domain, this method can easily be adapted to the frequency domain as well.

6. ACKNOWLEDGMENT

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