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Improved multiple description wavelet based image coding using subband uniform quantization

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ABSTRACT

The objective of multiple description coding (MDC) is to encode a source into multiple descriptions supporting different quality levels of reconstruction. In this paper, we use the multiple description transform coding (MDTC) algorithm based on the wavelet transform that has been shown to be robust to packet losses allowing a graceful quality degradation. The case of transmitting still images with four descriptions is considered. We propose to use subband uniform quantization with different quantization steps, optimized using a genetic algorithm (GA), when compressing to a target bit-rate. Simulation results show that the proposed method offers substantial improvements in the case of packet loss when compared to previously reported work that applies uniform quantization with a fixed step size.

1. Introduction and problem description

Multiple description coding (MDC) is a joint source-channel coding whose objective is to encode a source into several descriptions in such a way the quality of the recovered signal increases with the number of received descriptions. To accomplish this goal, each description alone must carry a sufficient amount of information about the original source. This necessarily means that there is a certain amount of common information and, hence, correlation between the descriptions.

Many approaches have been proposed to realise MDC. The first MD coder was designed by Vaishampayan [1] in which multiple description scalar quantizers were used in an extension of the old JPEG coder. Other methods for the design of MDC coders use correlation inducing transforms (multiple description transform coding: MDTC) [2–5]. Pereira et al. [6] and Sumohana et al. [7] have studied MDC techniques based on wavelet transform, but not considering correlating transforms in wavelet domain. A wavelet transform based MDTC coder for coding still images has been addressed by Khelil et al. [8].

The scheme proposed in [8], which constituted an improvement of the MDTC coder proposed by Goyal et al. [4,5], considers the transmission of images using MDTC based on wavelet transform for the case of four descriptions. The four generated descriptions (representing the four subbands obtained after applying a first level wavelet transform) are uniformly quantized with a constant quantization step. Unfortunately, we noticed that uniform quantization is performed within each subband with the same quantization step even though the four subbands do not have the same energy and they are not equally important.

In this paper, we propose to improve the technique described in [8] by using subband uniform quantization. The proposed approach employs four levels of quantization estimated according to the relative energy within each subband and are optimized heuristically with a genetic algorithm (GA) [9]. Simulation results show an improvement in the objective measure of peak signal to noise ratio (PSNR) and in the subjective perceptual quality of the reconstructed images.

The rest of this paper is organized as follows. In Section 2, we give a brief description of the multiple description transform coder. Section 3, presents our proposed wavelet transform based MDC coder. The optimization method using genetic algorithm is described in Section 4. The simulation results are presented in Section 5. Finally, some concluding remarks are given in Section 6.

2. Multiple description transform coding (MDTC)

Contrary to conventional transform coding (such as the DCT), where the transform is used to decorrelate the input image, the MDCT coding system uses a transform that introduce controlled amount of correlation among the transformed coefficients, based on linear transforms, mapping N input variables to N coefficients. The transform coefficients are partitioned into packets such that in case of packet loss, the lost coefficients can be estimated from the

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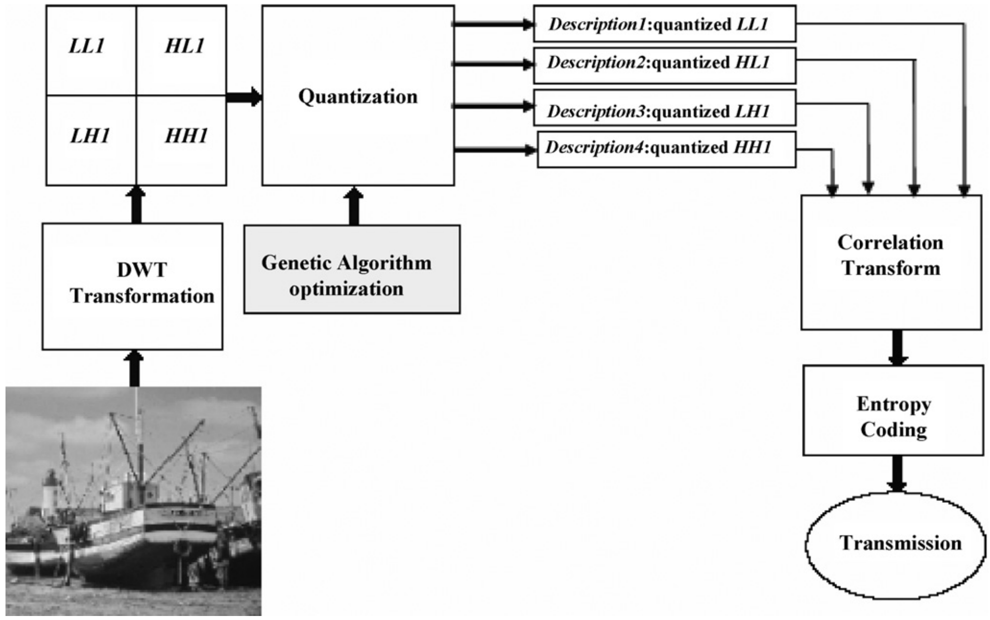

Fig. 1. MDTC DWT-based image coder with four descriptions.

received ones. Generally, the multiple description transform coding of a source vector x involves the following steps [8]:

1. Use a decorrelate transform (e.g. DCT, DWT, . . .);
2. Quantize the transformed coefficients;
3. Transform the quantized vector with a discrete transform;
4. Entropy code the resultant components.

When all components are received, the reconstruction process is to exactly invert the transform. The distortion is precisely the quantization error. If some coefficients are lost, they are estimated from the received coefficients using the statistical correlation introduced by the correlating transform. The estimation is then generated by inverting the transform as before. For more details of the coding and reconstruction procedures the reader is referred to [4,8].

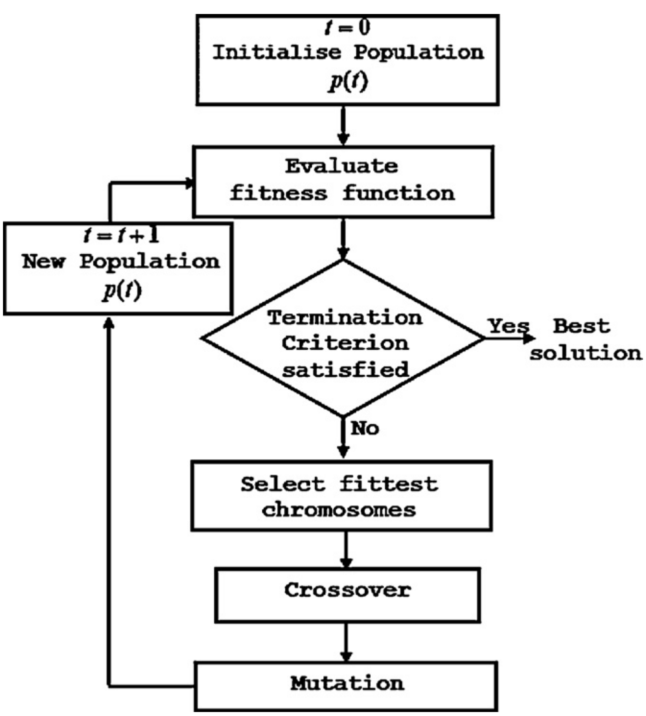

Fig. 2. Genetic algorithm flowchart.

3. Multiple description wavelet based coding using subband uniform quantization

Subband decomposition using discrete wavelet transform (DWT) is one of the best performing techniques among different transform based image coding techniques [9]. In this paper, the subband decomposition is done through the two-dimensional DWT using the Daubechies biorthogonal wavelet transform which is widely used in image compression [10,11] and also adopted in the JPEG2000 standard for image coding [12]. The first level of decomposition splits the image into four subbands consisting of one smooth LL subband, and three detail subbands, vertical HL subband, horizontal LH subband, and diagonal HH subband [12]. Inherently the wavelet decomposition concentrates most of the energy in the

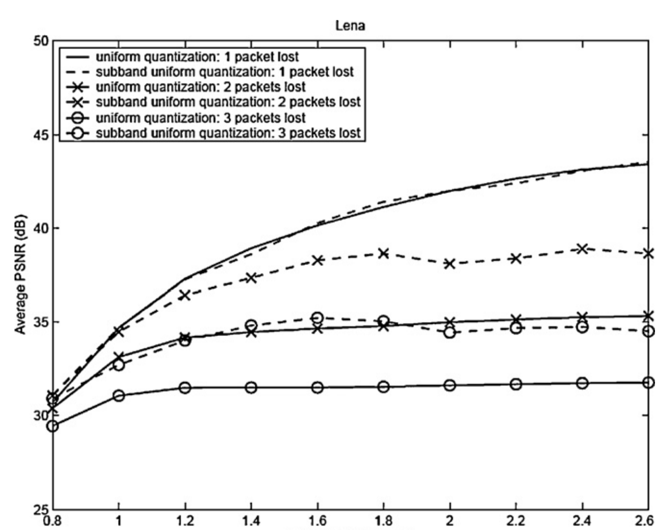

Fig. 3. Average PSNR versus bits per sample, 'Lena' image.

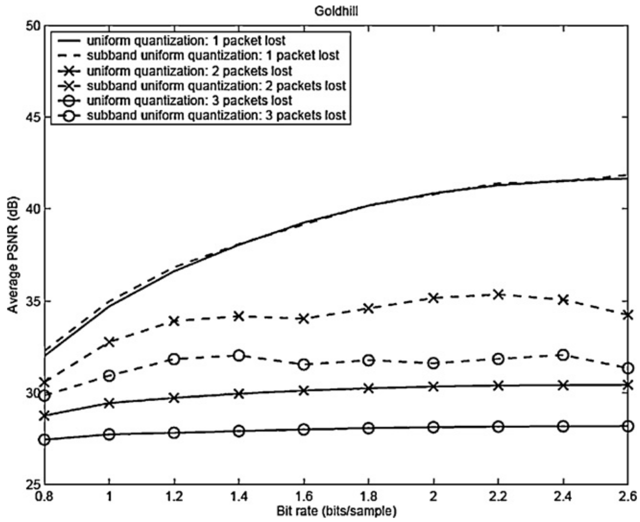

Fig. 4. Average PSNR versus bits per sample, 'Goldhill' image.

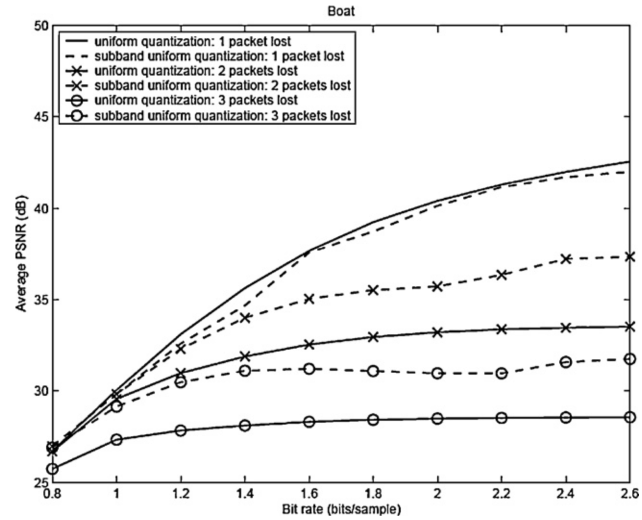

Fig. 5. Average PSNR versus bits per sample, 'boat' image.

LL subband, while the rest is distributed among all the three detail subbands with the least energy contained in the HH subband [9]. Therefore, this suggests the use of a uniform quantization scheme where the quantization step sizes are a function of subband energy. Consequently, the most important information (LL subband) can be quantized finely while the coefficients representing high frequency content (HH subband) can be quantized coarsely.

The MDTC/DWT coder, suggested in [8], is implemented as follows:

Fig. 6. Lena image reconstruction results for MDTC_DWT/UQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 46.88 dB); (b) reconstructed image from 3 received packets (PSNR = 43.12 dB); (c) reconstructed image from 2 received packets (PSNR = 36.12 dB); (d) reconstructed image from 1 received packet (PSNR = 32.67 dB).

Fig. 7. Lena image reconstruction results for MDTC_DWT/SUQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 43.96 dB); (b) reconstructed image from 3 received packets (PSNR = 41.97 dB); (c) reconstructed image from 2 received packets (PSNR = 38.09 dB); (d) reconstructed image from 1 received packet (PSNR = 34.44 dB).

1. The source image is transformed by the 1-level biorthogonal $B_{9/7}$ wavelet transform resulting in the four subbands: LL1, HL1, LH1, and HH1.

$$\begin{cases} \text{LL1} \rightarrow \text{description1} \\ \text{HL1} \rightarrow \text{description2} \\ \text{LH1} \rightarrow \text{description3} \\ \text{HH1} \rightarrow \text{description4} \end{cases}$$

2. The four vectors (descriptions) are formed.
3. The DWT coefficients (the four vectors) are uniformly quantized with a quantization step Δ.
4. Correlating transform is applied to the 4 vectors.
5. Entropy coding akin to that of JPEG is applied to the 4 vectors [5,8].

In step 2, we suggest to use subband uniform quantization based on the fact that the coefficients in different subbands will be quantized by uniform quantizers of different step sizes instead of uniform quantization with a constant quantization step. This DWT-based image coder is depicted in Fig. 1. Each subband or description des_i will be attributed a quantization step Δ_i. The problem is to determine, for a given bitrate, the set of quantization steps $\{\Delta_1, \Delta_2, \Delta_3, \Delta_4\}$ corresponding respectively to descriptions 1, 2, 3 and 4 that minimizes the reconstruction distortion in the case of packet losses. To ensure that the uniform quantization is performed according to the energy contained in each subband, the four quantization step sizes need to verify the relationship $\Delta_1 < \Delta_2 \leq \Delta_3 < \Delta_4$ or $\Delta_1 < \Delta_3 \leq \Delta_2 < \Delta_4$. We solve this optimization problem heuristically using a genetic algorithm (GA) approach described in the next section.

4. Optimization method using genetic algorithm

The genetic algorithm (GA) [13] is a well known method for solving both constrained and unconstrained optimization problems that is based on natural selection and natural genetics. Unlike many conventional optimization methods, which are generally single path searching algorithms, the GA starts searching from several points and evolves toward an optimal solution.

Given a target bitrate R_t, an outline of the genetic algorithm used to optimize the 4 quantization steps proceeds as follows:

1. Initial population
   We generate an initial random population of 20 chromosomes (suitable solutions for the problem). Each chromosome is a string corresponding to a vector of 4 quantization steps $\Delta = \{\Delta_i, i = 1, \ldots, 4\}$. So, in our case, the initial population is composed of 20 real valued vectors of size 4 each.
2. Fitness function
   Evaluate the fitness $f(\Delta)$ of each chromosome Δ in the population. The fitness function assigns to each individual in the

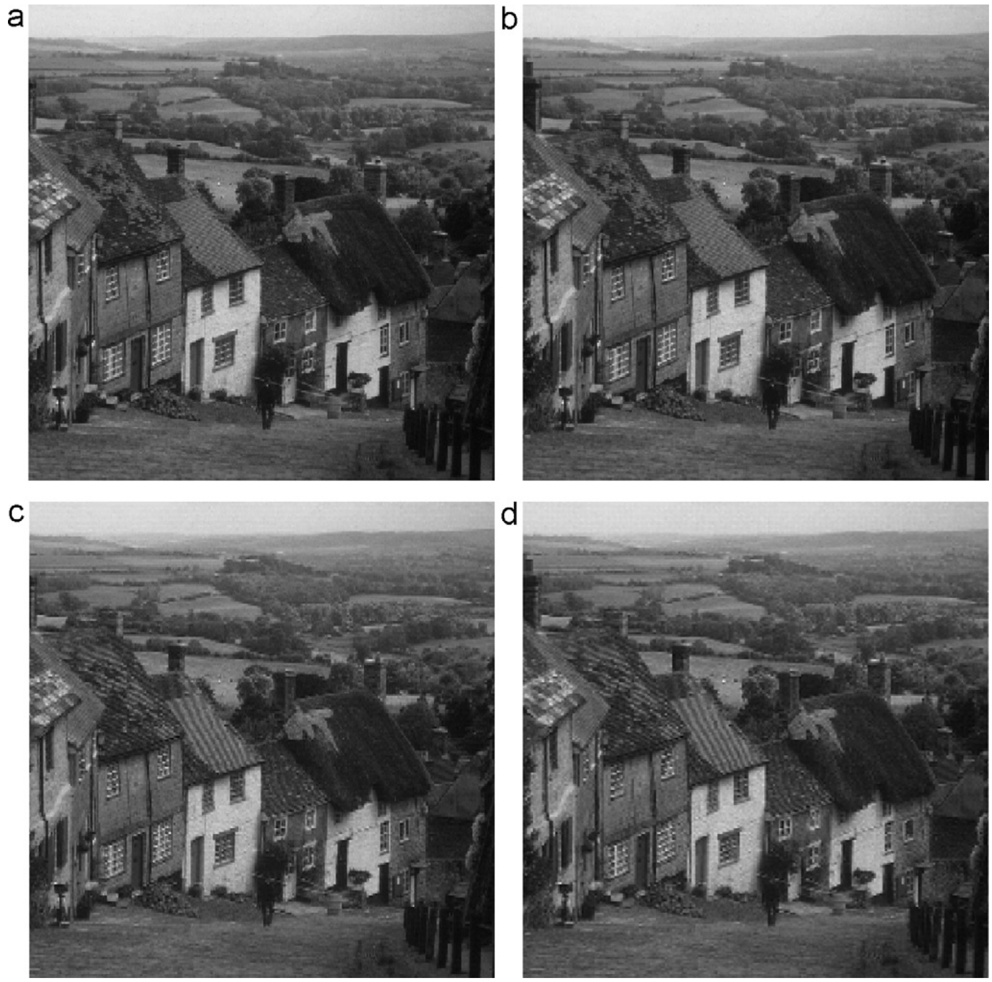

Fig. 8. Goldhill image reconstruction results for MDTC_DWT/UQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 46.80 dB); (b) reconstructed image from 3 received packets (PSNR = 40.86 dB); (c) reconstructed image from 2 received packets (PSNR = 30.34 dB); (d) reconstructed image from 1 received packet (PSNR = 28.12 dB).

population a numeric value that determines its quality as a potential solution. The fitness denotes the individual (chromosome) ability to survive and to produce offspring. In our case, the fitness is the square of the distance between the target bitrate R_t and the actual bitrate R_a:

$$f(\Delta) = (R_a(\Delta) - R_t)^2$$

subject to the constraints:

$$\begin{cases} \Delta_1 < \Delta_2 \leq \Delta_3 < \Delta_4 \\ \text{or} \\ \Delta_1 < \Delta_3 \leq \Delta_2 < \Delta_4 \end{cases}$$

3. Creating the next generation

At each step, the genetic algorithm uses the current population to create the children that makes up the next generation. The algorithm selects a group of individuals in the current population, called parents, who contribute their genes (entries of their vectors) to their children. In the GA we used, the roulette wheel selection is exploited [14]. The algorithm selects individuals that have better fitness values of parents.

In total, three types of children are generated:

(a) 'Elite' children are the individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation.

(b) 'Crossover' children are created by combining the vectors of a pair of parents. Scattered crossover with a crossover fraction equals to 0.8 is used in this paper [14]. Scattered crossover creates a random binary vector and selects the genes where the vector is a 1 from the first parent and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

(c) 'Mutation' children are created by introducing random changes, or mutations, to a single parent. In this work we have employed Gaussian mutation [14] where a random number is added to each vector input of an individual, which is taken from a Gaussian distribution centred at zero.

The above process is repeated until terminal conditions are satisfied; we denote the best chromosome as a solution, which is regarded as the optimal solution of the optimization problem. Fig. 2 shows the block diagram of the GA optimization process.

5. Simulation results

In order to verify the performance of the proposed quantization method, we apply the two previously mentioned quantization techniques to real images. Hence, we end up with two coders: the first one is the conventional MDTC/DWT based on uniform quantization with fixed step size referred to as MDTC_DWT/UQ, the second coder

Fig. 9. Goldhill image reconstruction results for MDTC_DWT/SUQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 44.91 dB); (b) reconstructed image from 3 received packets (PSNR = 40.79 dB); (c) reconstructed image from 2 received packets (PSNR = 33.58 dB); (d) reconstructed image from 1 received packet (PSNR = 31.60 dB).

Fig. 10. Boat image reconstruction results for MDTC_DWT/UQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 39.67 dB); (b) reconstructed image from 3 received packets (PSNR = 38.92 dB); (c) reconstructed image from 2 received packets (PSNR = 32.88 dB); (d) reconstructed image from 1 received packet (PSNR = 28.41 dB).

Fig. 11. Boat image reconstruction results for MDTC_DWT/SUQ at 2.0 bits/sample (a) reconstructed image from the 4 received packets (PSNR = 39.35 dB); (b) reconstructed image from 3 received packets (PSNR = 38.84 dB); (c) reconstructed image from 2 received packets (PSNR = 35.08 dB); (d) reconstructed image from 1 received packet (PSNR = 30.44 dB).

is the proposed MDTC/DWT based on subband uniform quantization referred to as MDTC_DWT/SUQ.

Redundancy of 0.1 bit/sample is evenly allocated to the four descriptions. The bit rate is estimated by sample scalar entropies.

Using the 512 × 512 'Lena', 512 × 512 'Goldhill' and 512 × 512 'boat' as test images, the comparison between the two uniform quantization methods can be better appreciated in Figs. 3–5, where, for each technique, the average PSNR is reported as a function of the bit rate for the cases of one, two and three packets dropped. From these curves, it can be seen that, in the case of one packet lost, both approaches yield the same results. Whereas, when two or three packets are lost the MDTC_DWT/SUQ technique generally outperforms MDTC_DWT/UQ in terms of PSNR as the bitrate increases. The average performance gains amount to an interesting value [15] of nearly 1.9 dB, 2.5 dB and 1.7 dB for Lena, Goldhill and boat images, respectively. Figs. 6–11 respectively compare the Lena, Goldhill and boat images reconstructed by both coders for the situations of 0, 1, 2, and 3 packet lost. It can be easily noticed that, using the new proposed coder MDTC_DWT/SUQ, the visual quality is significantly improved.

However, the MDTC_DWT/SUQ based on GA tends to be slow with respect to the MDTC/DWT coder suggested in [8] because of the GA iterative process that involves many candidate solutions. This is primarily due to the fitness function, which is a very important part in most GA, but it is the weakest link which usually requires the most amount of time to run. In our simulation, the GA evaluates the fitness candidate solution using $f(\Delta) = (R_a(\Delta) - R_t)^2$ and this takes at most $L^2 + L$ multiplications and $2 \times L$ additions for and $L \times L$ image. Conducting many experiment runs, an average number of fitness evaluations, in estimating the quantization steps, is about 600 evaluations per GA execution is obtained for the three 512 × 512 test images used. Therefore, the required numbers of operations are $1000 \times (L^2 + L)$ multiplications and $1000 \times (2 \times L)$ additions. Using a 512 × 512 image, the total number of operations required for the optimization of the quantization steps is about 160 millions operations which is insignificant as an emerging specialized digital signal processors (DSP) using FPGAs (field-programmable gate array) can deliver over 1 TeraMACS (10^{12} multiply-accumulates per second) [15–18].

6. Conclusion

In this paper, we have proposed a new MDTC wavelet transform based scheme for robust image coding and transmission through unreliable networks for the case of four descriptions. The main novelty lies in the fact that the considered coder applies a subband uniform quantization (with four quantization steps) to the four descriptions instead of using a uniform quantizer with a fixed quantization step. The proposed quantization strategy takes into account the importance of the LL subband (representing the first description) obtained after application of the wavelet transform. In addition, a GA based optimization approach is employed to optimize the quantization steps for minimizing the reconstruction distortion in the case of packet losses. The proposed scheme has been applied to typical test images, where it has been shown to improve the image quality reconstruction both objectively and subjectively compared to our recently reported approach employing uniform quantization with a fixed step size [8].

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