

# Central Decoding for Multiple Description Codes based on Domain Partitioning

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**Abstract.** Multiple Description Codes (MDC) can be used to trade redundancy against packet loss resistance for transmitting data over lossy diversity networks. In this work we focus on MD transform coding based on domain partitioning. Compared to Vaishampayan’s quantizer based MDC, domain based MD coding is a simple approach for generating different descriptions, by using different quantizers for each description. Commonly, only the highest rate quantizer is used for reconstruction. In this paper we investigate the benefit of using the lower rate quantizers to enhance the reconstruction quality at decoder side. The comparison is done on artificial source data and on image data.

## Keywords

multiple description coding, domain based, scalar quantization, reconstruction, central decoder

## 1. Introduction

Multiple description coding (MDC) is a source coding technique which can be used for transmitting data over lossy diversity networks. The MDC generates two or more different descriptions, which are sent over different channels of the network. Each of these descriptions can be decoded independently. The reconstruction quality at the receiver increases with the number of received descriptions. Decoding one description is usually called side decoding. Decoding more than one description is usually called central decoding. If all descriptions need the same bandwidth and all side-decoder outputs are of the same quality, the descriptions are called balanced. For a scenario displayed in figure 1 the theoretical limits for a gaussian source with zero mean and unit variance are derived in [3].

A popular approach for MDC uses the indices of an arbitrary quantizer for a mapping procedure called index assignment [8]. For this approach it is difficult to allocate redundancy for three or more descriptions in an optimal way, as mentioned in [6]. Partitioning based MDC avoids this problem, by using quantizers with different rates for generating the side descriptions [1]. As an additional benefit such

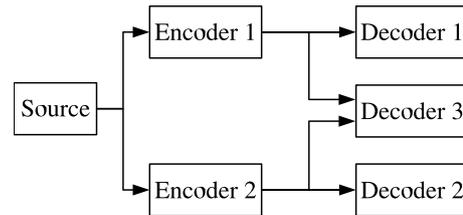


Fig. 1. A multiple description scenario with two senders and three receivers.

approaches may also generate standard conform descriptions [7]. For such multiple description schemes there are several ways for central decoding, which are compared in this paper. The paper is structured as follows: In section two, three different ways for reconstruction at the central decoder are introduced. In section three, the test scenario is explained and experimental results are shown. In section four, the results are summarized.

## 2. MDC based on Domain Partitioning

In domain partitioning based MDC the MD encoders are scalar quantizers with different quantization intervals. This results in different quantization errors for each description, as shown in figure 2:

$$y_i = x + q_i$$

This simple approach can easily be generalized to  $N$  de-

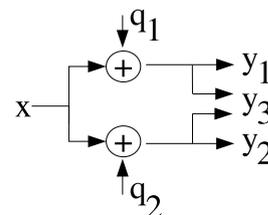


Fig. 2. Domain based MDC,  $q_i$  = quantization error corresponding to a quantization interval  $\Delta_i$ .

scriptions with  $N$  uniform scalar quantizers. The proportion between the different quantization intervals adjust the redun-

dancy. High redundancy corresponds to nearly equal sized quantization intervals:

$$\frac{\Delta_i}{\Delta_j} \approx 1$$

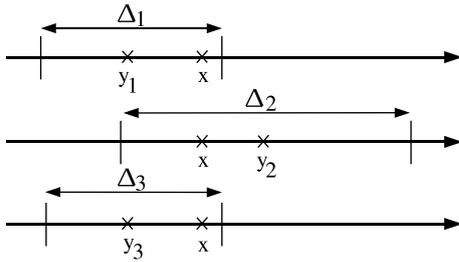
Low redundancy corresponds to high differences between the quantization intervals:

$$\frac{\Delta_i}{\Delta_j} \gg 1$$

These  $N$  quantizers generates  $N$  sets of indices that describes the source data. Balanced descriptions are achieved by switching these indices by a scheme, known to encoder and decoder.

## 2.1. Highest Rate Reconstruction

The simplest and most common way for central decoding uses only the description with the highest rate for each quantization index. Ignoring the lower rate descriptions leads to easily predictable central distortion and low complexity.



**Fig. 3.** Source sample  $x$  with two corresponding quantization intervals  $\Delta_1, \Delta_2$ . Quantization interval  $\Delta_3$  results from highest rate decoding. Reconstruction values  $y_1, y_2$  and  $y_3$  are chosen for an uniformly distributed source.

## 2.2. Reconstruction by Linear Superposition

It is possible to reduce the quantization error of the central decoder by using more descriptions than only the highest rate description. For this we introduce  $N$  weighting factors  $\alpha_i$ , and construct the central reconstruction by weighted superposition of the received side reconstructions. With

$$1 = \sum_{i=1}^N \alpha_i \Leftrightarrow \alpha_N = 1 - \sum_{i=1}^{N-1} \alpha_i, \quad (1)$$

the central decoder can be written as:

$$\begin{aligned} y &= \sum_{i=1}^N \alpha_i y_i \\ \Rightarrow y &= x + \sum_{i=1}^N \alpha_i q_i \end{aligned}$$

To maximize the reconstruction quality, we minimize the following term:

$$\begin{aligned} E\{(y-x)^2\} &= E\left\{\left(\sum_{i=1}^N \alpha_i q_i\right)^2\right\} \\ (E\{\cdot\}) &\triangleq \text{statistical expectation} \end{aligned}$$

As a first approximation, we assume that  $q_i$  and  $q_j$  are uncorrelated for  $i \neq j$ . As a matter of fact this is not true, especially for  $\frac{\Delta_i}{\Delta_j} = k, k \in \mathbb{N}$ . In section 3 we will show that even with this raw assumption an enhancement for central decoding is possible for high redundancy.

$$\Rightarrow E\{(y-x)^2\} = \sum_{i=1}^N E\{(\alpha_i q_i)^2\}$$

Condition (1) reduces the dimension of this problem by one:

$$\begin{aligned} E\{(y-x)^2\} &= \sum_{i=1}^{N-1} \alpha_i^2 E\{q_i^2\} \\ &\quad + \left(1 - \sum_{i=1}^{N-1} \alpha_i\right)^2 E\{q_N^2\} \end{aligned}$$

Minimization of quantization error by zero setting the derivation for each  $\alpha_i$ :

$$\begin{aligned} \frac{\delta E\{(y-x)^2\}}{\delta \alpha_i} &\stackrel{!}{=} 0 \\ \Rightarrow \alpha_i &= \frac{E\{q_N^2\}}{E\{q_i^2\}} \left(1 - \sum_{i=1}^{N-1} \alpha_i\right) \quad (2) \end{aligned}$$

The solution of these  $N-1$  equations minimizes the quantization error.

As an example for two dimensions, (1) and (2) leads to:

$$\begin{aligned} \alpha_1 &= \frac{E\{q_2^2\}}{E\{q_1^2\} + E\{q_2^2\}} \\ \alpha_2 &= \frac{E\{q_1^2\}}{E\{q_1^2\} + E\{q_2^2\}} \end{aligned}$$

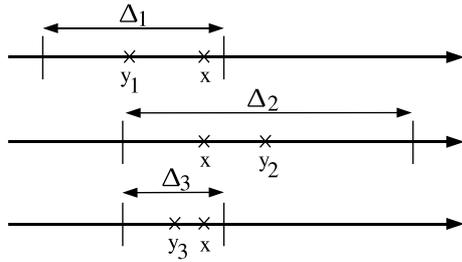
## 2.3. Intersection Reconstruction

A more deterministic way of using the lower rate descriptions to enhance the quality of the central decoder output is shown in [4] for DPCM systems. Each received quantization index belongs to one quantization interval with one lower limit  $L_i$ , and one upper limit  $U_i$ . For each quantizer, the following applies:

$$x \in (L_i, U_i) \quad (3)$$

By applying more than one quantizer intervals, formula (3) becomes:

$$x \in (\max(L_i), \min(U_i)), \forall i$$



**Fig. 4.** Source sample  $x$  with two corresponding quantization intervals  $\Delta_1, \Delta_2$ . Quantization interval  $\Delta_3$  results from intersection decoding. Reconstruction values  $y_1, y_2$  and  $y_3$  are chosen for an uniformly distributed source.

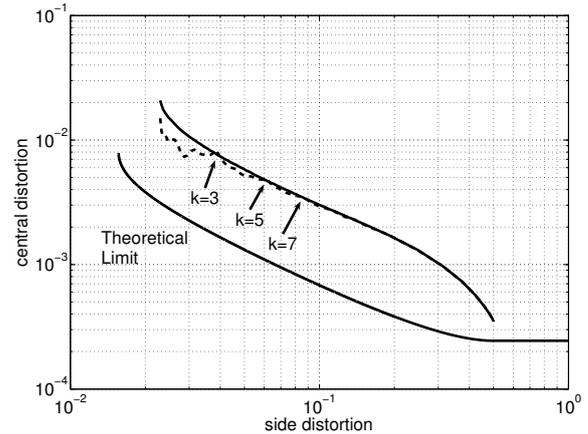
By reducing the width of the reconstruction interval the distortion at the decoder decreases and  $y$  approximates the source sample more accurate. This decoding approach results in no quality improvement if all limits of the higher rate quantizer are also limits of the lower rate quantizer. This may happen in the case of  $\frac{\Delta_i}{\Delta_j} = k, k \in \mathbb{N}$ , depending on the width of the quantizer deadzone. In all other cases every received quantizer index may reduce the width of the reconstruction interval for the central decoder.

### 3. Experimental Results

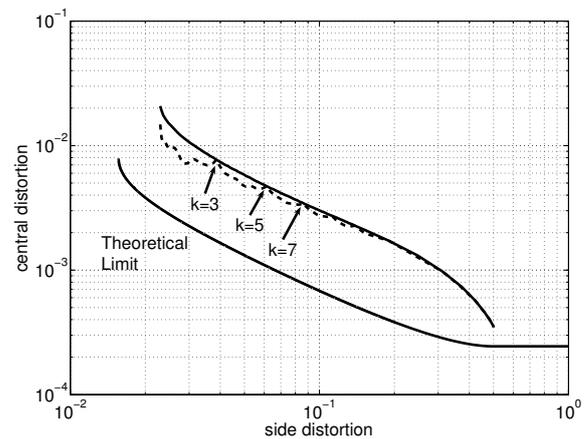
For low complexity, all simulations are limited to two descriptions and three decoders, as shown in figure 1. First a gaussian source with zero mean and unit-variance is used as source data for comparison of the three decoders. The two encoders are uniform scalar quantizer with different quantization intervals  $\Delta_i$ . For balanced descriptions, the two sets of quantization indices are mixed by a codec wide known scheme, e.g. the scheme used in [6]. The rate is approximated by the entropy of the indices. Cause of the high rate of 2 bps we assume uniformly distribution of the quantization error.

Results are shown in figure 5 and figure 6, along with the theoretical limit for multiple description coding of a gaussian source as derived in [3]. Figure 5 shows that in the case of  $\frac{\Delta_2}{\Delta_1} = k = 2n + 1, k, n \in \mathbb{N}$  the linear superposition method gets worse than the highest rate method. In these cases the assumption of no cross-correlation between quantization errors of different descriptions does not apply. For these cases, figure 6 shows the same quality for highest rate and intersection reconstruction. This is because the limits of the lower rate quantization intervals are also limits of the higher rate quantization intervals when using uniform scalar quantizer without a wider deadzone.

Second, the wavelet coefficients of some commonly used test images are used as sourcedata for the MDC. Generating the two descriptions is done similar as by the gaussian source. Entropy coding is performed by the SPIHT algorithm [5]. For visualization and comparison of the efficiency of MDCs redundancy rate distortion Plots (RRD-Plots), intro-



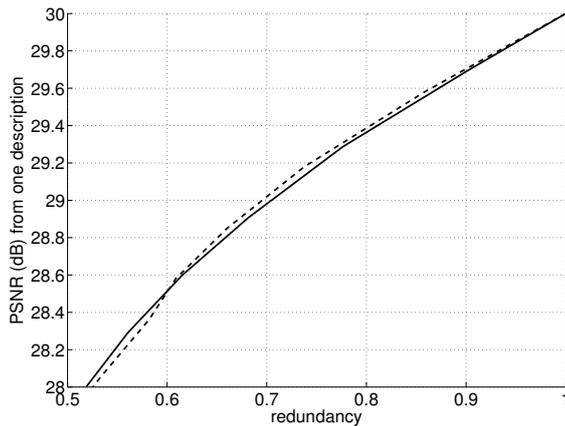
**Fig. 5.** Highest rate decoder (solid line) vs. linear superposition decoder (dotted line), gaussian source with unit-variance and zero mean, Rate: 2bps.



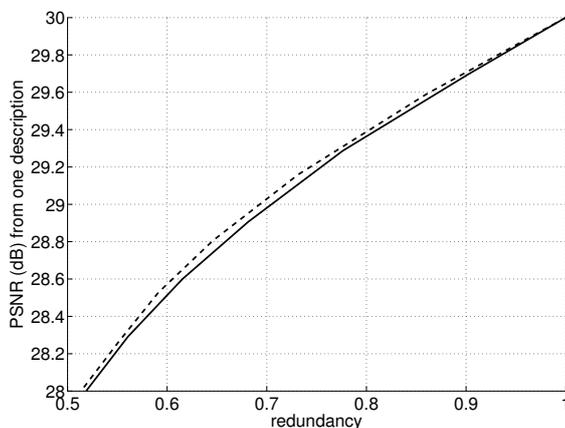
**Fig. 6.** Highest rate decoder (solid line) vs. intersection decoder (dotted line), gaussian source with unit-variance and zero mean, Rate: 2bps.

duced by [9], are used. The experimental results for image *Lena* 512x512 are shown in Figure 7 and 8. With other test images, comparable results are achieved.

As by the gaussian source figure 7 shows that the linear superposition method improves the highest rate reconstruction only for high redundancy. For a redundancy of 0.6 or less the assumption of uncorrelated quantization errors  $q_i$  seems wrong. In figure 8, no such drawback can be seen. The intersection reconstruction improves every domain based MDC, and may be even more effective for more than two descriptions, because every different quantizer results in additionally limits of quantization intervals, which can be interpreted at the central decoder.



**Fig. 7.** Lena 512x512, highest rate decoder (solid line) vs. linear superposition decoder (dotted line), PSNR for central decoder: 30dB.



**Fig. 8.** Lena 512x512, highest rate decoder (solid line) vs. intersection decoder (dotted line), PSNR for central decoder: 30dB.

## 4. Conclusions

In this paper it is shown how to utilize the lower rate quantizers for reducing the distortion at the central decoder in a domain based partitioning MDC. The linear superposition and the intersection method are described for  $N$  possible descriptions, so they can be used in domain based partitioning MDC systems with arbitrary number of descriptions. For the first approach, called linear superposition, less complexity is traded for the possibility of drawbacks. For lower redundancy, the assumption of negligible cross correlation between the quantization errors of the different channels may not apply.

The second, more complex approach is at least as good as the highest rate reconstruction, and by proper choosing of quantization intervals, a significant reduction of the distortion at the central decoder is possible.

Although the intersection method is better than the linear superposition method, there may be applications where the

quantization intervals may not be known at the decoder, for example [2]. For such applications the linear superposition may be an improvement for an environment with need of high redundancy.

Further investigations may interpret the cross correlation of the linear superposition method or study the benefits of these central decoders for more than two channels.

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