Filter Banks for Prediction-Compensated Multiple Description Coding

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Abstract

This paper investigates the design and application of the optimal filter banks for a prediction-compensated multiple description coding (PC-MDC) scheme, where the coefficients in each subband are split into two descriptions. Each description also includes the prediction residuals of the data in the other description. The optimal designs of orthogonal and biorthogonal filter banks with multiple-level decompositions are formulated in a unified framework. The optimal results in all cases are found to be very close to the optimal filter banks in traditional single description coding. This allows us to apply the proposed method to existing systems with single-description-optimized filter banks and still enjoy near-optimal performance. Image coding results in the JPEG 2000 framework show that the proposed method achieves similar or better performance than other methods. It also has lower complexity and is more compatible to the JPEG 2000 standard.

I. Introduction

Multiple description coding (MDC) [1] is an attractive technique of combating transmission errors. In MDC, the source signal is encoded into several coded streams called descriptions, which are sent to the receiver via different network paths. An arbitrary subset of descriptions can be used to reconstruct the original signal, and the reconstruction quality improves with the number of descriptions received.

In this paper, we focus on the case with two descriptions and three decoders, where the decoders receiving one and two descriptions are called the *side decoder* and the *central decoder*, respectively. In particular, we study the wavelet-based MD image coding, for which various methods have been proposed. For example, in [2], a two-stage modified multiple description scalar quantizer (MMDSQ) is developed. Its application in wavelet-based MD image coding yields better results than previous methods. However, the side decoder result of the MMDSQ is not satisfactory at low redundancy. In [3], each code-block in JPEG 2000 is coded at two bit rates, which are included into two descriptions, respectively. The Lagrangian method is used to find the optimal data partition and bit allocation. A feature-oriented method is proposed in [4], where the least square-based prediction is used to identify wavelet coefficients that are difficult to predict, and these coefficients are encoded directly. However, this requires side information to be sent to

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the decoder to identify the coding mode for each coefficient. In addition, both [3] and [4] require complicated optimization, which increases the complexity of the algorithms.

To improve the side decoder performance, it is proposed in [5] to encode the prediction residual of the other description in each description. However, no image coding result is reported in [5]. Recently, a prediction-compensated MDC (PC-MDC) framework [6] is developed. Although the method is similar to [5], the design and implementation in [6] are much simpler, and superior image coding performance over [2] is obtained.

Most wavelet-based MDC schemes use the existing wavelet transform directly, which may not be optimal. This prompts the study of the optimal two-band filter banks or wavelets for multiple description coding. In [7], the output of each subband is used to form one description. The lost description is estimated from the received one using linear prediction. The optimal orthogonal and biorthogonal filter banks are designed. A similar approach is developed in [8], where the correlating transform in [9] is generalized to the frequency domain. However, their side decoder performances are also not satisfactory at high rates. Moreover, to facilitate the prediction between the two subbands, the two subband filters increasingly resemble each other as the increase of the redundancy, making them quite different from the existing filter banks for single description coding (SDC). In addition, only one-level decomposition is considered in [7], [8]. Therefore their methods cannot be applied satisfactorily to existing wavelet-based systems.

In this paper, we generalize the prediction-compensated MDC method in [6] to two-band filter banks and formulate the design of the optimal orthogonal and biorthogonal prediction-compensated multiple description filter banks (PC-MDFB) with multi-level decomposition in a unified framework. In our method, the two descriptions are formed by the even-indexed and odd-indexed parts of all subbands, respectively, which is different from [7], [8]. Design examples show that the optimal filter banks are very similar to their single description counterparts. Therefore existing wavelet transforms can be applied directly with near-optimal performance. Moreover, our method encodes the prediction residual of the other description in each description. It resolves the problem of poor side decoder performance at high rates, which is associated with many prediction-only approaches, and hence yields lower side distortion than [7], [8]. The application of the proposed scheme in JPEG 2000 based multiple description image coding demonstrates that our method achieves similar or better performance than [2] and [3]. Our method also has lower complexity and stays highly compatible with JPEG 2000 framework.

II. The Optimal Multi-level Filter Bank

A. System Overview

Fig. 1 shows the encoder block diagram of generating two descriptions in the proposed prediction-compensated multiple description filter bank framework with one-level decomposition. The input signal $x(n)$ is processed by a two-band perfect reconstruction filter bank with analysis and synthesis polyphase matrices $\mathbf{H}(\omega)$ and $\mathbf{G}(\omega)$, respectively, where $\mathbf{G}(\omega)\mathbf{H}(\omega) = \mathbf{I}$. The two subband filters of $\mathbf{H}(\omega)$ and $\mathbf{G}(\omega)$ are denoted as $H_i(z)$ and $G_i(z)$ $(i = 0, 1)$, respectively.

When M-level decomposition is used for two-band filter banks, $M+1$ subband signals $y_i(n)$ $(i = 0, ..., M)$ are generated. In the proposed prediction-compensated multiple description coding method, the output of each subband is split into the even-indexed part and the odd-indexed part. The results are denoted as $y_{ij}(n)$ $(i = 0, \ldots, M, j = 0, 1)$. The

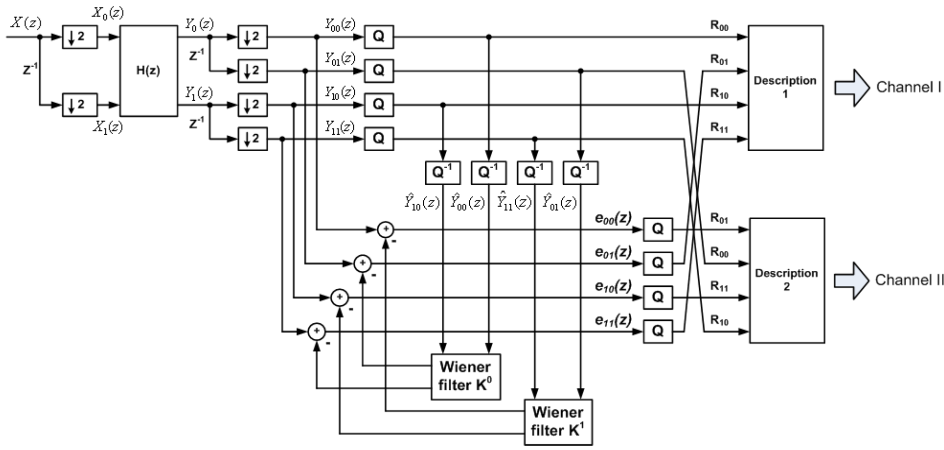


Fig. 1. Prediction compensated MDC for filter bank outputs.

even (odd) parts of all subbands are coded into Description 1 (2), with a bit rate of R_{i0} for coefficients from Subband i. In analogy to the intra-frames in video coding, we refer to these coefficients as the *intra-coded coefficients* of each description. In addition, each description also uses the reconstructed intra-coded coefficients to predict the intra-coded coefficients of the other description via Wiener filtering, and the prediction residuals are encoded in each description as redundant information, with a bit rate of R_{i1} for the residual of Subband i. R_{i1} is usually much lower than R_{i0} for correlated sources. We call these predictively coded coefficients *inter-coded coefficients*, similar to the inter-coded frames in video coding.

This partition ensures that two balanced descriptions are generated, and the bit rate per description is

$$R = \frac{1}{2(M+1)} \sum_{i=0}^{M} (R_{i0} + R_{i1}). \tag{1}$$

At the decoder side, if both descriptions are received, the decoded intra-coded coefficients from the two descriptions are combined to obtain the reconstructed signal. The bits for inter-coded coefficients in each description are simply discarded. If only one description is received, the missing coefficients are first estimated from the received intra-coded coefficients by Wiener filtering. The decoded prediction residuals are then added to the estimation before applying the synthesis filter bank.

B. Optimal Filter Bank Design

In this part, we formulate the design of the optimal filter bank for the proposed scheme. We first derive the details of the prediction and various distortions in the system. The input signal is assumed to be a wide-sense stationary (WSS) correlated Gaussian random sequence with a known power spectral density (p.s.d.) $S_X(\omega)$. Its 2×2 polyphase p.s.d. matrix is

$$\mathbf{S_{XX}}(\omega) = \begin{bmatrix} S_{X_0X_0}(\omega) & S_{X_0X_1}(\omega) \\ S_{X_1X_0}(\omega) & S_{X_1X_1}(\omega) \end{bmatrix}, \tag{2}$$

where $S_{X_iX_j}(\omega)$ is the p.s.d. function between polyphases $x_i(n)$ and $x_j(n)$.

We first consider one-level decomposition. Denote $\mathbf{y}(n) = [y_0(n) \;\; y_1(n)]^T$ as the analysis filter bank output and let $\mathbf{S_{YY}}(\omega)$ be its p.s.d. matrix. Likewise, $\mathbf{S_{\hat{Y}\hat{Y}}}(\omega)$ and

$\mathbf{S}_{\hat{\mathbf{X}}\hat{\mathbf{X}}}(\omega)$ are the p.s.d. matrices of the synthesis filter bank input and output. We have the following relationships [10], [11]

$$\begin{aligned} \mathbf{S}_{\mathbf{YY}}(\omega) &= \mathbf{H}(\omega)\mathbf{S}_{\mathbf{XX}}(\omega)\mathbf{H}(\omega)^H, \\ \mathbf{S}_{\hat{\mathbf{X}}\hat{\mathbf{X}}}(\omega) &= \mathbf{G}(\omega)\mathbf{S}_{\hat{\mathbf{Y}}\hat{\mathbf{Y}}}(\omega)\mathbf{G}(\omega)^H. \end{aligned} \tag{3}$$

To generate two descriptions, we downsample each subband into the even-indexed part and the odd-indexed part. It is easy to show that after downsampling $y_0(n)$ and $y_1(n)$, the p.s.d. functions between $Y_{ij}(\omega)$ and $Y_{kl}(\omega)$ can be written as

$$\begin{aligned} S_{Y_{i0}Y_{k0}}(\omega) = S_{Y_{i1}Y_{k1}}(\omega) &= \frac{1}{2}\left(S_{Y_iY_k}(\frac{\omega}{2}) + S_{Y_iY_k}(\frac{\omega}{2}+\pi)\right), \\ S_{Y_{i0}Y_{k1}}(\omega) = S^*_{Y_{k1}Y_{i0}}(\omega) &= \frac{e^{j\frac{\omega}{2}}}{2}\left(S_{Y_iY_k}(\frac{\omega}{2}) - S_{Y_iY_k}(\frac{\omega}{2}+\pi)\right), \end{aligned} \tag{4}$$

where $i, k = 0, 1$.

When M-level decomposition is used for two-band filter banks, $M+1$ subband signals $y_i(n)$ $(i = 0, ..., M)$ are generated. By the noble identity [11], the corresponding equivalent subband filters are obtained as follows

$$\begin{aligned} \bar{H}_k(z) &= \begin{cases} \prod_{n=0}^{M-k-1} H_0(z^{2^n}), & k = 0, \\ H_1(z^{2^{M-k}})\prod_{n=0}^{M-k-1} H_0(z^{2^n}), & k = 1, ..., M. \end{cases} \\ \bar{G}_k(z) &= \begin{cases} \prod_{n=0}^{M-k-1} G_0(z^{2^n}), & k = 0, \\ G_1(z^{2^{M-k}})\prod_{n=0}^{M-k-1} G_0(z^{2^n}), & k = 1, ..., M. \end{cases} \end{aligned} \tag{5}$$

In our method, the linear minimum mean-squared error (LMMSE) filter or Wiener filter is used to predict the missing data [7]. The Wiener filter for inter-coded coefficients in Description 1 is given by

$$\mathbf{K}^0(\omega) = \begin{bmatrix} S_{Y_{01}Y_{00}}(\omega) & \cdots & S_{Y_{01}Y_{M,0}}(\omega) \\ \vdots & \ddots & \vdots \\ S_{Y_{M,1}Y_{00}}(\omega) & \cdots & S_{Y_{M,1}Y_{M,0}}(\omega) \end{bmatrix} \times \begin{bmatrix} S_{Y_{00}Y_{00}}(\omega) & \cdots & S_{Y_{00}Y_{M,0}}(\omega) \\ \vdots & \ddots & \vdots \\ S_{Y_{M,0}Y_{00}}(\omega) & \cdots & S_{Y_{M,0}Y_{M,0}}(\omega) \end{bmatrix}^{-1}, \tag{6}$$

where $S_{Y_{ij}Y_{kl}}(\omega)$ is the p.s.d. function between $Y_{ij}(\omega)$ and $Y_{kl}(\omega)$, which can be derived from the input statistics by recursively computing the p.s.d. of each subband signal using (3) and (4). The Wiener filter for Description 2 can be obtained similarly. As discussed in [10], [12], the quantization noise is ignored in designing the Wiener filter.

The filter in (6) uses all data of one description to predict each coefficient in the other description. In addition, it generally leads to IIR filter. A simplification using FIR time-domain Wiener filter, which is more suitable for practical applications, is derived in [13], where one block of subband outputs $\mathbf{y}_{B,i}(n) = [y_{0i}(n) \dots y_{Mi}(n)]^T$, $i = 0, 1$, is predicted from its $2L$ neighboring reconstructed blocks $\hat{\mathbf{y}}_{B,1-i,L}(n) = [\hat{\mathbf{y}}^T_{B,1-i}(n-L) \dots \hat{\mathbf{y}}^T_{B,1-i}(n+L-1)]^T$, *i.e.*, L blocks of causal neighbors and L blocks of anti-causal neighbors, similar to [6].

We now look at the encoding of Description 1, in which $y_{i0}(n)$ is intra-coded and $y_{i1}(n)$ is predictively coded. Define $g_i^2 = \frac{1}{2\pi}\int_{-\pi}^{\pi} |\bar{G}_i(\omega)|^2 d\omega$. For paraunitary filter banks, $g_i^2 = 1$. Since $y_{i0}(n)$ is WSS Guassian, at high rates, the reconstruction error per sample caused by the quantization after synthesis filtering is [7], [10], [11]

$$D_{i0} = \bar{g}_i^2 2^{-2R_{i0}} \exp\left(\frac{1}{2\pi}\int_{-\pi}^{\pi} \log S_{Y_{i0}Y_{i0}}(\omega)d\omega\right) \triangleq 2^{-2R_{i0}} w_{i0}^2, \tag{7}$$

where

$$\bar{g}_i^2 = \begin{cases} \frac{1}{2^{(M-i)}} g_i^2, & i = 0, \\ \frac{1}{2^{(M-i+1)}} g_i^2, & i = 1, \dots, M. \end{cases} \tag{8}$$

Each $y_{i1}(n)$ is predicted using all reconstructed intra coefficients $\hat{y}_{i0}(n)$'s. The p.s.d. of the prediction errors of $y_{i1}(n)$ is given by

$$S_{e_{i1}}(\omega) = S_{Y_{i1}Y_{i1}}(\omega) - \mathbf{K}_i^0 [S_{Y_{00}Y_{i1}}(\omega), \cdots, S_{Y_{M,0}Y_{i1}}(\omega)]^T, \tag{9}$$

where $\mathbf{K}_i^0$ is the i-th row of $\mathbf{K}^0(\omega)$.

Since $y_{i1}(n)$ is predictively coded, its quantization error equals that of the residual $e_{i1}(n)$ [10]. Therefore the reconstruction error per sample after synthesis filtering is

$$D_{i1} = \bar{g}_i^2 2^{-2R_{i1}} \exp\left(\frac{1}{2\pi}\int_{-\pi}^{\pi} \log S_{e_{i1}}(\omega)d\omega\right) \triangleq 2^{-2R_{i1}} w_{i1}^2. \tag{10}$$

In Description 2, $y_{i1}(n)$ is intra-coded while $y_{i0}(n)$ is predictively coded. The average distortions for Description 2 and 1 are equal since our method generates balanced descriptions.

When both descriptions are received in our scheme, the intra-coded coefficients are used in the reconstruction, and the corresponding average distortion per sample (*the central distortion*) is

$$D_0 = \sum_{i=0}^{M} D_{i0}. \tag{11}$$

If only one description is available, a half of the coefficients of $y_i(n)$ are intra-coded and the rest are inter-coded. The average distortion (*the side distortion*) is

$$D_1 = \frac{1}{2}\sum_{i=0}^{M} (D_{i0} + D_{i1}). \tag{12}$$

Let p be the probability of losing one description, the expected distortion is

$$D = p^2\sigma_x^2 + 2p(1-p)D_1 + (1-p)^2 D_0. \tag{13}$$

As in many MDC systems, our objective is to minimize the expected distortion D subject to the bit rate constraint (1). Using Lagrangian method with high rate assumption, we get

$$\begin{aligned} R_{i0} &= R + \frac{1}{4(M+1)}\log_2 \frac{w_{i0}^{4(M+1)}}{p^{(M+1)}\prod_{j=0}^{M} w_{j0}^2 w_{j1}^2}, \\ R_{i1} &= R + \frac{1}{4(M+1)}\log_2 \frac{p^{(M+1)} w_{i1}^{4(M+1)}}{\prod_{j=0}^{M} w_{j0}^2 w_{j1}^2}. \end{aligned} \tag{14}$$

$$D = p^2\sigma_x^2 + 2(1-p)(M+1)\sqrt{p w_0 w_1} 2^{-2R}. \tag{15}$$

where w_0 and w_1 are geometric means of all w_{j0}^2 and w_{j1}^2, respectively.

It can be seen from (15) that to minimize the expected distortion we need to minimize the term $w_0 w_1$, which is proportional to the geometric mean of the energies of the intra-coded signals and prediction residuals. This term only depends on the filter bank and the input. Therefore the optimal filter bank does not depend on either the channel loss probability or the redundancy requirement at high rates. This is a highly desired feature since we can design one optimal filter bank and apply it to all scenarios.

Another widely used criterion is minimizing the *single-channel distortion* $D_s = D_1 - \frac{D_0}{2}$ under a redundancy constraint $\rho = 2R - R^*$, where R^* is the minimum rate to achieve a distortion of D_0 in single description coding. This criterion has been adopted in schemes such as [7], [8]. Although in general these two optimization approaches not necessarily lead to the same optimal filter bank, we show in [13] that they are indeed equivalent in the proposed framework at high rates and high redundancy. This is another attractive property of our method.

C. Design Examples with AR(1) signals

In this part, we design the optimal MD filter bank for the first order autoregressive (AR(1)) sequence with correlation coefficient r, whose p.s.d. function is [10]

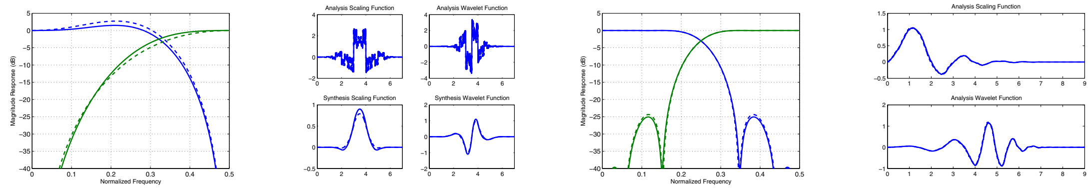
$$S_X(\omega) = \frac{\sigma_x^2(1-r^2)}{1 - 2rcos(\omega) + r^2}. \tag{16}$$

For a given filter bank with $\mathbf{H}(\omega)$ and $\mathbf{G}(\omega)$, following the previous derivation, we can compute the expected distortion at a given bit rate. The Matlab optimization routine *fminsearch* is then used to find the optimal filter bank that minimizes the distortion. Note that although the channel loss probability is required to compute the expected distortion, it does not affect the optimization result at high rates. In the following, two design examples are given for AR(1) sources with correlation coefficient $r = 0.95$ and $\sigma_x^2 = 1$. The bit rate is chosen to be $R = 2$ bits/sample/description.

The first example is a 2-band linear phase perfect reconstruction filter bank (LPPRFB) with one-level decomposition using the type-II lattice in [14]. It is designed with one vanishing moment in the analysis filter bank and two vanishing moments in the synthesis filter bank. The FIR time domain Wiener filter [13] of size 2×4 is used. The frequency responses and scaling/wavelet functions of the optimal 8-tap LPPRFBs for MDC and SDC are compared in Fig. 2 (a-b). The SDC LPPRFB is optimized for coding gain. The coding gain of the optimal MDC and SDC LPPRFBs are 6.24 dB and 6.39 dB, respectively.

Fig. 2 (c-d) show another design example of a 2-band 10-tap paraunitary filter bank (PUFB) [11] with 5-level decomposition and one vanishing moment. An important observation is that in both examples the optimal filter banks for the proposed MDC scheme resemble their counterparts in the single description coding very well. This suggests that we can directly apply the proposed method to existing practical wavelet based image coding systems such as the JPEG 2000 without having to change the wavelet transform.

To study the performance of the proposed method, we design a 2-band, 8-tap LPPRFB with one-level decomposition using the frequency domain Wiener filter in (6) for AR(1) sources with correlation coefficient $r = 0.9$ and compare it with the optimal IIR biorthogonal and orthogonal solutions in Fig. 9 and Table II of [7] (denoted as FB-MDC). The



(a) (b) (c) (d)

Fig. 2. (a-b): 8-tap optimal LPPRFB for PC-MDC (solid lines) and SDC (dashed lines). (a) Frequency responses. (b) Scaling and wavelet functions. (c-d) The optimal 10-tap, 5-level PUFB for PC-MDC (solid lines) and SDC (dashed lines). (c) Frequency responses. (d) Scaling and wavelet functions.

comparison is fair since the same R-D function and input signal model are used. The results are shown in Fig. 3 (a). It can be seen that our method has similar single-channel distortion D_s at low redundancy while achieves lower D_s at high redundancy, despite the additional FIR and linear phase constraints. This is consistent with the performance of the improved MD transform coding in [5]. Fig. 3 (a) also shows that D_s of FB-MDC cannot be arbitrarily reduced due to the presence of the prediction error. For example, the smallest D_s of the orthogonal FB-MDC in [7] is 0.0525 with a redundancy of 0.2967 nats/sample. The smallest D_s of the biorthogonal FB-MDC is 0.0374, but it can only be achieved with infinite redundancy [7]. This problem is resolved in our method by encoding the prediction residual.

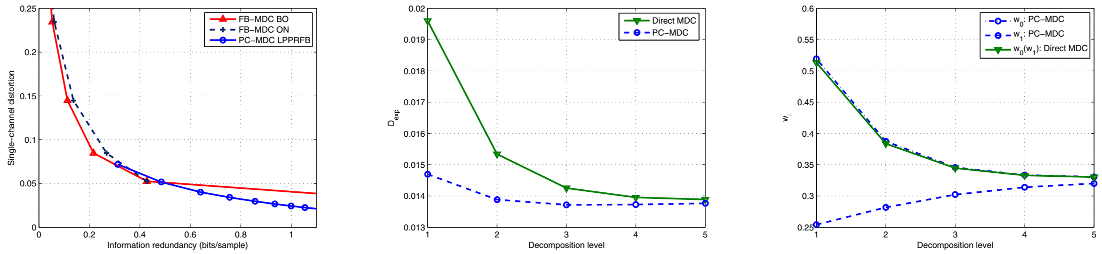
To gain further insight of the multi-level PC-MDFB, we compare the expected distortions of a 6-tap PUFB for an AR(1) source at different decomposition levels with that of the direct MDC method in Fig. 3 (b). In direct MDC, each subband output is partitioned into even-indexed and odd-indexed coefficients. The even(odd) part is intra-coded in Description 1(2). Instead of sending the prediction residual, a coarsely-quantized version of the odd(even) part is included in Description 1(2). This method can be viewed as a counterpart of the direct coding method in [3] under our framework. Our method shows significant advantage, especially when the decomposition level is from 1 to 3.

In Fig. 3 (b), it is interesting to note that the performance of the proposed method does not always increase with the number of decomposition levels. Three-level decomposition is optimal in this example. We also observe similar behaviors for biorthogonal PC-MDFBs and other filter banks such as Daubechies' orthogonal wavelets, the 5/3 and 9/7 wavelets. The best performance is usually given by three or four levels of decompositions.

To explain this, we start from (15), which shows that the optimized expected distortion increases with $w_0 w_1$. The w_0 and w_1 curves of our method and the direct MDC method are given in Fig. 3 (c). The result shows that as the number of decomposition levels M increases, the w_0 of our method decreases due to improved decorrelation, whereas w_1 increases, since the reduced correlation also decreases the prediction efficiency. Therefore there is an optimal M with the minimal $w_0 w_1$. The w_0 curve of the direct MDC is slightly lower than our method, but its w_1 curve is much higher, leading to worse overall performance. This illustrates the trade-off between the filter bank coding performance and the prediction efficiency. Our method sacrifices a small amount of intra-coding efficiency but significantly reduces the prediction error and the expected distortion.

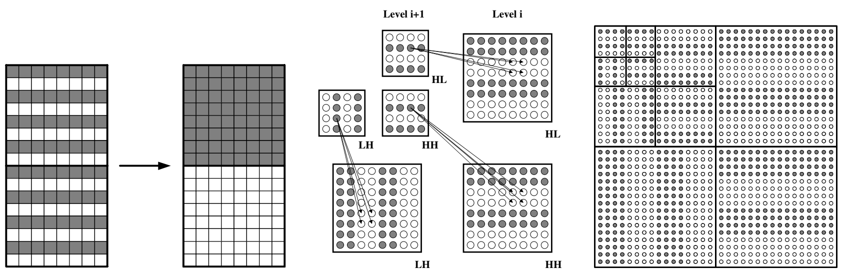
III. Applications in Image Coding

In this section, we implement the prediction-compensated multiple description coding algorithm in the JPEG 2000 framework without changing the underlying wavelet trans-



(a) (b) (c)

Fig. 3. (a) The redundancy (ρ) vs. single-channel distortion (D_s) curves of PC-MDC and the orthogonal (FB-MDC ON) and biorthogonal FB-MDC (FB-MDC BO) in [7]. (b) The expected distortions of different MDC schemes with optimized 6-tap PUFBs, bit rate R = 2 bits/sample/description, and loss probability p = 0.1. (c) The w_0 and w_1 curves of different MDFB schemes.



(a) (b) (c)

Fig. 4. Subband partitions and prediction. (a) Horizontal partition. (b) Parent-children prediction. (c) Tree partition.

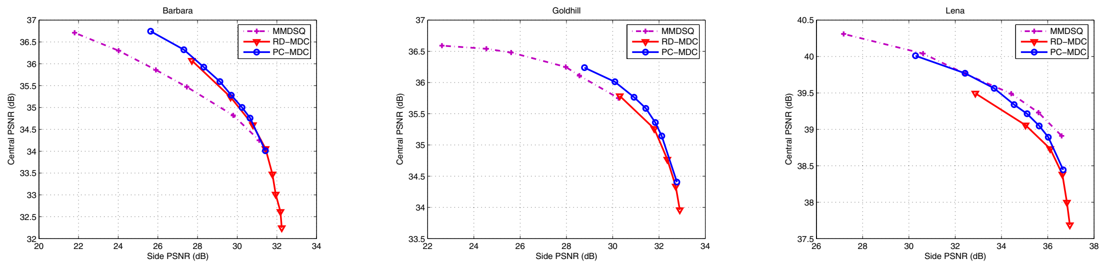
form. The OpenJPEG JPEG 2000 codec [15] is used. The source codes and executable files of our modified codec can be downloaded from [16]. The performance of our method is compared with that of two state-of-the-art wavelet methods in the literature, *i.e.*, the MMDSQ in [2] and the Lagrangian based RD-MDC in [3], whose codec is available at [17].

To generate two descriptions, each subband of a wavelet transformed image in JPEG 2000 is split into two parts, which are grouped separately and partitioned into codeblocks for the intra and inter coding.

The LL subband is split into even and odd-indexed lines and then grouped separately as shown in Fig. 4 (a). Each inter-coded coefficient is predicted by the average of the two nearest intra coefficient neighbors. The partition is slightly different from that in our theoretical model, but experimental results show that it yields a better tradeoff between the prediction performance and the adverse impact to the JPEG 2000 entropy coding.

The HL, LH and HH subbands are encoded by using the parent-children tree partition and prediction illustrated in Fig. 4 (b). Fig. 4 (c) gives a partition example of a 32×32 wavelet transformed image. To take advantage of the different edge capturing capabilities of different subbands and to minimize the impact to the JPEG 2000 entropy coding, the LH subband is split into vertical slices while the HL and HH subband are split into horizontal slices. A parent intra coefficient (dark dot) in level $i+1$ is down-scaled as the estimate of the four children (white dots) in level i. The scaling factor is fixed for each subband and is chosen from 1/8 to 1/256 by experiments. The only exception is that the inter coefficients of the highest level HL, LH and HH subbands are coded directly, because the prediction for them using the simple scaling method is not helpful.

The rate control in our method is as follows. Given the target bit rate and redundancy



(a) (b) (c)

Fig. 5. Tradeoff between the central and the side PSNRs for PC-MDC, RD-MDC and MMDSQ at R = 0.5 bpp/description. (a) Barbara; (b) Goldhill; (c) Lena.

ratio ρ_r = (inter bit rate) / (intra bit rate), the corresponding intra and inter bit rates can be calculated. The JPEG 2000 rate control is then used to encode all intra codeblocks at the target bit rate. We then use the reconstructed intra coefficients to encode the residual codeblocks at its target bit rate. Since we use symmetric coefficient-level splitting with pre-defined patterns, balanced descriptions is achieved with very low complexity.

Our method is more preferable in terms of compatibility and complexity. The only extra work in our method is to produce the necessary intra codeblocks and residual codeblocks. All modules of JPEG 2000 can be reused and good performance and balanced descriptions are easily achieved. In contrast to this, the quantization scheme in the MMDSQ is incompatible with the JPEG 2000. Although the RD-MDC is compatible with JPEG 2000, it has very high complexity. To find the optimal data partition, the RD-MDC exhaustively searches all possible combinations of codeblocks. For example, the total number of codeblocks of a 256×256 images with 5-level wavelet transform is 25 and therefore 2^{25} combinations need to be tested. Fast algorithms can reduce the search time but degrade the performance as well [3].

Some simulation results at rate R = 0.5 bpp/description are given in Fig. 5, for three 512×512 standard test images with different characteristics. Five levels of resolution have been used. The codeblock size is 64×64. Compared with the RD-MDC in [3], the proposed PC-MDFB method can achieve similar or better performance for all three test images. Given the same central PSNR, the side PSNR of our method is up to 3 dB and 1 dB better than that of the MMDSQ and the RD-MDC, respectively. Fig. 6 shows several decoding results of our method (PC-MDC) and RD-MDC when one description is lost. The two methods are compared at the same bit rate and similar central PSNRs. It can be seen that our method yields better side PSNR and preserves more texture details, as exemplified by the roof in Goldhill and the clothes in Barbara.

IV. Conclusions

This paper studies the optimal multi-level filter bank design for prediction-compensated multiple description coding (PC-MDC). We formulate the problem for correlated Gaussian sources. Orthogonal and biorthogonal design examples with the AR(1) sources show that the optimal solutions are very close to the optimal single description filter banks, and they do not depend on either the channel loss rate or the redundancy. These properties enable us to apply the PC-MDC to existing single description filter banks with near-optimal performance. Image coding results in the JPEG 2000 framework show that the proposed

(a) (b) (c) (d)

Fig. 6. Side decoder results with 0.5 bpp/description in (a-b) and 0.125 bpp/description in (c-d). The central PSNR and redundancy ratio ρ_r are listed in the parentheses. (a) Goldhill by RD-MDC: 30.30 dB (35.78 dB, $\rho_r = 5\%$); (b) Goldhill by PC-MDC: 31.05 dB (35.80 dB, $\rho_r = 14\%$); (c) Barbara by RD-MDC: 19.91 dB (28.18 dB, $\rho_r = 5\%$); (d) Barbara by PC-MDC: 20.98 dB (28.19 dB, $\rho_r = 1\%$).

method achieves similar or better performances than existing methods in the literature. It also has lower complexity and is highly compatible with JPEG 2000.

The image coding performance of the proposed framework can be further improved. For example, more advanced predictions can be used to reduce the prediction residual, and the side information can be reduced by refining the entropy coding for the inter-coded coefficients.

V. Acknowledgement

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