Optimal Filtering of Wavelet-based Multiple Description Image Coding Using Correlating Transforms

K. Khelil, T. Bouadjila, F. Berrezzek
Univ. Souk Ahras, Fac. Sci & Tec.,
LEER Lab.,
Souk Ahras (41000), Algeria.
k_khelil@yahoo.fr, khaled.khelil@univ-soukahras.dz

Abstract— **The objective of multiple description coding (MDC) is to encode a single information source into multiple bitstreams, in a manner that the reconstructed source can be produced at different qualities according to the amount of bitstreams received at the decoder. In this paper, we propose to employ an optimal filtering strategy as a post processing method for a multiple description transform coding (MDTC) approach which utilizes discrete wavelet transform (DWT). Experimental results show that the proposed approach provides better results compared to existing approaches in the literature.**

Keywords— Multiple description transform coding, optimal filtering, discrete wavelet transform, post-processing.

I. INTRODUCTION

Nowadays the sharing of multimedia information such as image or video over packet switched networks like the Internet is growing fast. Therefore, when transmitting data over such unreliable networks, packet losses and sometimes complete channel failures are practically inevitable. Moreover, packet loss and time delay may cause serious problems in applications that require real time data transmission, and may lead to a severe degradation of the received signal [1]. To alleviate these problems, multiple description coding (MDC) aim at splitting a data source into multiple bitstreams, called descriptions [2, 3]. The MDC coder is designed so that each description can be independently decoded, and the quality of the recovered signal increases smoothly with the number of received descriptions.

In the literature, there are several different MDC approaches that have different redundancy adding schemes and complexity. The multiple description scalar quantization (MDSQ) approach proposed by Vaishampayan [4], creates descriptions using index assignment. The method in [5], which is referred to as polyphase downsampling (PD), performs encoding by adding redundancy to subsampled data to make the system robust in case of packet loss. These methods have also been applied to video coding [6-8]. PCT based MDC approaches, used in image coding, can be broadly classified into two main categories. The first class addresses MDTC for the case of two descriptions in the DCT domain [9]-[11]. A generalization of the scheme presented in [11], to more than two descriptions, is described in [12]. The approach falling into the second category uses a correlating transform in the discrete wavelet transform (DWT) domain instead of the DCT [13], [14]. In real applications, different network paths may have dissimilar channel capacities. Accordingly, Saitoh and Yakoha [15] suggested a scheme, referred to as ratio configurable multiple description correlating transform coding (RMDCTC), where the data size is adjusted among the descriptions to fit the inequality of channel bandwidth. Based on compressive sensing (CS), the authors in [16] proposed a rather new MDC approach for the case of two descriptions. In this technique, the input image is divided into two sub-images using quincunx downsampling and then DWT is applied to generate the two descriptions. In [17], the issue of designing near optimal down-sampling filter and interpolation filters, to improve block-based coders such as JPEG, is explored. It has been shown that using such a scheme may results in significant improvement over existing approaches.

In this paper, it is proposed to use an optimal filtering approach with the wavelet based MDTC technique reported in [13] to improve the reconstruction quality of the source image. In this method, least-squares estimation is utilized to obtain the filter coefficients [17] minimizing the difference between encoded and original data, for each description.

In other words, packets that are lost, due to channel failures, are generated using the received descriptions and the quality of the image, obtained by combining all the descriptions, is enhanced further through optimal filtering.

The rest of the paper is organized as follows. In Section two, the wavelet-based MDTC coder is examined and the proposed optimal filtering based scheme is described. Experimental results are presented in the third section and finally conclusions are provided.

II. OPTIMAL FILTERING OF WAVELET-BASED MDTC

A. Image Coding using Wavelet-based MDTC

Generally, in conventional transform coding, the transformation is used in order to decorrelate the input variables [8]. Here, the transformation is applied to embed a certain degree of correlation among the transformed coefficients to enable estimation of lost components from the received ones [9]-[11]. The MDTC scheme, for the case of four descriptions, presented in [13] is illustrated in Fig. 1. First, DWT transformation and uniform quantization are applied to each block of N independent, zero-mean variables with different variances to produce block of N transformed coefficients. Then, using a correlating transform, statistical correlation is added among the previously obtained transformed components (descriptions). Finally, the different descriptions are entropy coded and transmitted over erasure channel. Such DWT-based multiple description approach is referred to as MDTC/DWT coder [13].

B. Description of the proposed scheme

The key idea of the proposed approach in this paper is to combine the MDTC DWT-based technique of [13] with the optimal filtering approach given in [17]. Detailed description of the proposed scheme is given in Fig. 2. Initially a 1-level DWT using 9/7 biorthogonal filters [19] is applied to the original input image to obtain four subbands, referred to as LL, HL, LH and HH. Secondly, uniform quantization is applied to all subbands, and four descriptions $\{D_1, D_2, D_3, D_4\}$ are then created through a pairwise correlating transform T as:

$$\begin{bmatrix} D1 \\ D2 \\ D3 \\ D4 \end{bmatrix} = \mathbf{T} \begin{bmatrix} LL_q \\ LH_q \\ HL_q \\ HH_q \end{bmatrix} \tag{1}$$

The components $LL_q, LH_q, HL_q,$ and HH_q represent uniform quantized uncorrelated subbands obtained after application of DWT. The pairwise correlating transform T allows adding statistical correlation among the descriptions $\{D_1, D_2, D_3, D_4\}$, so that lost descriptions may be reasonably computed from the received ones. For example, the descriptions D1, D3, and D4, when lost, may be reconstructed using the received description D2. After correlating transformation, the four descriptions $\{D_1, D_2, D_3, D_4\}$ are entropy coded and sent over lossy channel.

Simultaneously, at the encoding stage, descriptions are grouped using a description lost selector T_i , where $i =$ 1 to 4, for all possible loss combinations. Note that there are fourteen different loss scenarios for the case of four descriptions. In other words, the lost description selector simulates all the 14 loss possibilities during transmission in order to compute the corresponding 14 optimal filter kernels which will be multiplexed with the four descriptions and communicated reliably through some other means. Therefore, for each loss scenario, lost descriptions are estimated from the received ones, and subbands ($\widehat{LL}_q$, $\widehat{LH}_q$, $\widehat{HL}_q$, $\widehat{HH}_q$) are formed using inverse pairwise correlating transform. Then, uniform dequantization and inverse DWT are employed to obtain a reconstructed image $\tilde{I}$.

Hence, the coefficients of each optimal filter are computed as described in [17]. Minimizing the difference between original image I and reconstructed image $\tilde{I}$, the filter kernel G_n of size lxl is obtained through The Iterative Preconditioned Conjugate Gradients method (IPCG) [20, 21] based on least square estimation:

$$\min_{G_n} \left\| I - \hat{I} \right\|_2^2 = \min_{G_n} \left\| I - \tilde{I} * G_n \right\|_2^2 \tag{2}$$

where $*$ denote 2-D convolution operation.

At the receiver, the image is reconstructed using the received descriptions and optimal filtering. First, the lost descriptions are estimated using the received ones. Then, all the descriptions are combined together to reconstruct the entire image, simply, by performing the inverse operations of the encoder. Finally, optimal filtering is applied to improve the reconstructed image quality.

$$\hat{I} = \tilde{I} * G_n \tag{3}$$

Here, $\tilde{I}$ *and* $\hat{I}$ represent respectively the reconstructed image and the enhanced image after optimal filtering.

III. EXPERIMENTAL RESULTS

In this section the performance of our optimal filtering MDTC coder, referred to as MDTC/DWT-OPT, is compared to the existing MDTC/DWT approach presented in [13]. In order to show the efficiency of the proposed scheme, numerical simulations have been carried out employing images 'Lena', 'Barbara', 'Peppers' and 'Goldhill' of dimension 512 × 512. In these experiments, the cases of 0, 1, 2 and 3 description loss are considered, and a target coding bitrate in the range of $0.6 - 2.0$ bpp is used. The corresponding plots for the different test images and for all packet loss cases are reported in Fig. 3-6. From the obtained results, it can be easily noticed that our proposed coder allows better reconstruction quality in case of description loss.

For the case of one description lost, the two schemes exhibit practically the same performance. Whereas, if two or three descriptions are lost, an average gain of nearly 2 dB is observed for the four test images used. Moreover, evaluating the performance for the "Barbara" image, which has rich texture and edge information, shows that our method performs significantly better thanks to the optimal filtering approach. The situation is similar for the "Pepper" image, which mostly contains smooth textures. In order to show visual effect of the optimal filtering approach, Fig. 7 illustrates visual results for the "Barbara" test image encoded at 1.6 bpp for the case of three descriptions lost. It can be seen that our technique achieves better reconstruction of textures and edges compared to MDTC/DWT.

IV. CONCLUSION

In this article, we have introduced the combination of PCT based MDC which utilizes DWT as the transform coding approach and optimal filtering method. The optimal filter coefficients computed at the encoder are multiplexed into the descriptions and utilized at the decoder by simply performing linear filtering. The proposed coder has been applied on four typical test images. Through simulation experiments, a considerable improvement in image reconstruction quality is obtained by the proposed MDTC/DWT-OPT approach compared to the MDTC/DWT coder.

REFERENCES

[1] Lee, Y-C, Kim, J., Altunbasak, Y., & Mersereau, R. M., (2003). Layered Coded vs. Multiple Description Coded Video over Error-Prone Networks. Signal Processing: Image Communication, 18(5), 337–356.

[2] Goyal, V. K., (2001). Multiple Description Coding: Compression Meets the Network. IEEE Signal Processing Magazine, 18(5), 74-93.

[3] El-Gamal, A. A., & Cover, T. M., (1982). Achievable Rates for Multiple Descriptions. IEEE Trans. on Information Theory, 28, 851-857.

[4] Vaishampayan, V. A., (1993). Design of Multiple Description Scalar Quantizers. IEEE Trans. on Information Theory, 39(3), 821-834.

[5] Franchi, N., Fumagalli, M., & Lancini, R., (2002). Flexible Redundancy Insertion in a Polyphase Down Sampling Multiple Description Image Coding. IEEE International Conference on Multimedia and Expo, 605-608.

[6] Campana, O., Contiero, R., & Mian, G.A., (2008). An H.264/AVC Video Coder based on Multiple Description Scalar Quantizer. IEEE Trans. on Circuits and System Video Technology, 18(2), 268-272.

[7] Adedoyin, S., Fernando, W.A.C., & Karim, H.A., Hewage, C.T.E.R., & Kondoz, A.M., (2008). Scalable Multiple Description Coding with Side Information Using Motion Interpolation. IEEE Trans. Consumer Electron., 54(4), 2045-2052.

[8] N. Franchi, Multiple Description Video Coding for Scalable and Robust Transmission over IP, IEEE Transactions on Circuits and Systems for Video Technology, Volume 15 Issue 3, March 2005

[9] Wang, Y., Orchard, M., & Reibman, A., (2001). Multiple Description Coding using Pairwise Correlating Transforms. IEEE Trans. on Image Processing, 10(3), 351–366.

[10] Wang, Y., Orchard, M., & Reibman, A., (1997). Multiple Description Image Coding for Noisy Channels by Pairing Transform Coefficient. IEEE first workshop MMSP97, 419–24.

[11] Orchard, M., Wang, Y., Vaishampayan, V., & Reibman, A., (1997). Redundancy Rate-Distortion Analysis of Multiple Description Image Coding using Pairwise Correlating Transforms. IEEE International Conference on Image Proceedings, 608–611.

[12] Goyal, V.K., & Kovacevic, J., (2001). Generalized Multiple Description Coding with Correlating Transforms. IEEE Trans on Information Theory, 47(6), 2199–2224.

[13] Khelil, K., Bekka, R. E., Djebarri, A., & Rouvaen, J. M., (2007). Multiple Description Wavelet-Based Image Coding Using Correlating Transforms. Int. Journal of Electronics and Communications (AEÜ), 61(6), 411-417.

[14] Khelil, K., Hussain, A., Bekka, R.E., & Berrezzek, F., (2011). Improved Multiple Description Wavelet Based Image Coding Using Subband Uniform Quantization. Int. Journal of Electronics and Communications (AEÜ), 65(11), 967-974.

[15] Saitoh, D., & Yakoh, T., (2011). Ratio Configurable Multiple Description Correlating Transform Coding. Industrial Technology (ICIT), 352-357. Industrial Technology (ICIT), 2011 IEEE International Conference on

[16] Danhua, L., Dahua, G., & Guangming, S., (2011). A New Multiple Description Image Coding Scheme Based on Compressive Sensing. Communication Technology (ICCT), 385-388. Communication Technology (ICCT), 2011 IEEE 13th International Conference on

[17] Tsaig, Y., Elad, M., Milanfar, P., & Golub, G. H., (2005). Variable Projection for Near-Optimal Filtering in Low Bit-Rate Block Coders. IEEE Trans. on Circuits and Systems for Video Technology, 15(1), 154-160.

[18] Mallat, S., (1989). A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. IEEE Trans Pattern Anal Mach Intell., 11(7), 674–693.

[19] Daubechies, I., (1992). Ten Lectures on Wavelets. doi:10.1137/1.9781611970104.

[20] Hestenes, M.R., & Stiefel, E., (1952). Methods of Conjugate Gradients for Solving Linear Systems. Journal of Research of the National Bureau of Standards, 49(6), 409-436.

[21] [21] Romero, S., & Romero, L.F., (2002). An Optimized Preconditioned Conjugate Gradient Algorithm. Technical Report No: UMA-DAC-02/11, University of Malaga.

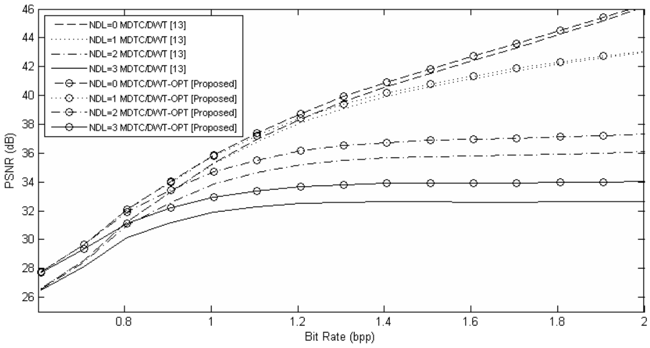

Fig. 3 MDC results for Lena test image.

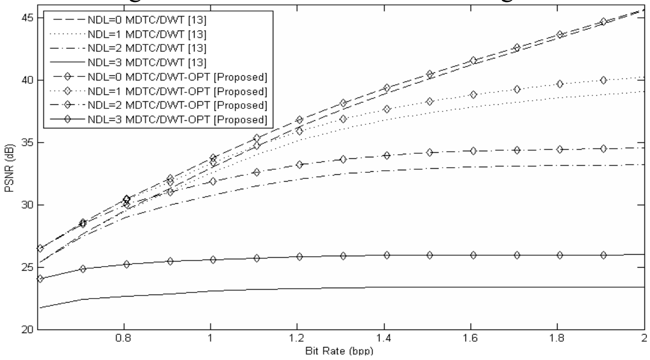

Fig. 4 MDC results for Barbara test image.

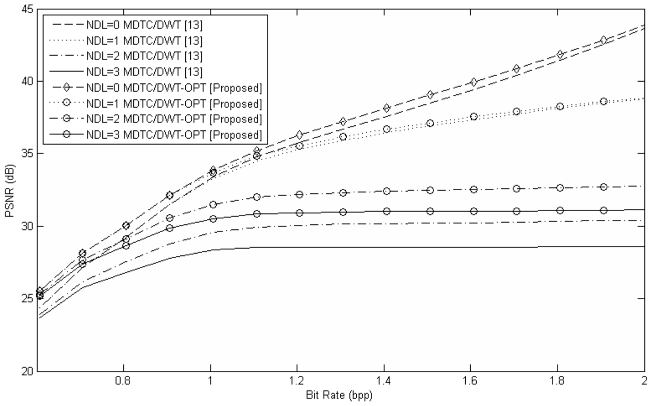

Fig. 5 MDC results for Peppers test image.

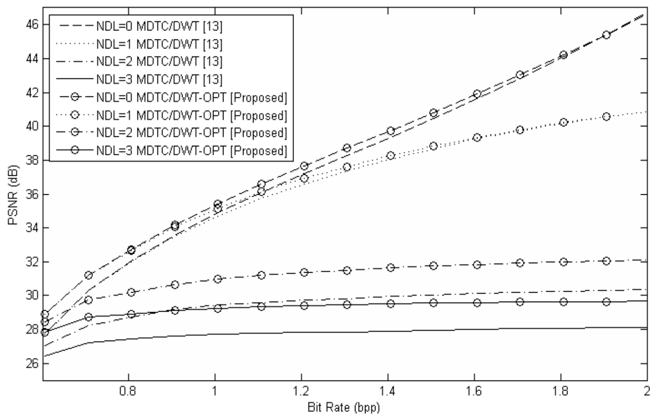

Fig. 6 MDC results for Goldhill test image.

(a) Original

(b) 3 descriptions lost PSNR=23.38dB [13]

(c) 3 descriptions lost PSNR=25.96dB (Proposed)

Fig. 7 Visual results for optimal filtering based MDC approach.

.