ARTICLE IN PRESS

Available online at www.sciencedirect.com

ScienceDirect

Int. J. Electron. Commun. (AEÜ) ■■■ (■■■) ■■■–■■■

International Journal of Electronics and Communications AEÜ

www.elsevier.de/aeue

LETTER

Multiple description wavelet-based image coding using correlating transforms

Khaled Khelil[a,*], Raïs El Hadi Bekka[b], Ali Djebarri[a], Jean M. Rouvaen[c]

[a]Laboratoire LTTNS, Université de Djillali Liabes, 22000 Sidi Bel Abbés, Algeria
[b]Dépt. d'Electronique, Université de Ferhat Abbés, 19000 Sétif, Algeria
[c]IEMN-UMR CNRS 8520, Dépt. OAE Université de Valenciennes Le Mont-Houy, Valenciennes Cedex 59313, France

Received 1 October 2005

Abstract

The objective of multiple description coding (MDC) is to represent a source into multiple descriptions such that various reconstruction qualities are obtained from different subsets of the descriptions. In this paper, we propose a simple scheme that combines the multiple descriptions transform coding (MDTC) method with the discrete wavelet transform (DWT). We compare the performance of the proposed scheme with a discrete cosine transform (DCT)-based scheme prevalent in other papers. Simulation results show that our proposed DWT technique outperforms both objectively and subjectively the method based on DCT in the case of packet loss.

Keywords: Joint source channel coding; Multiple description coding; Discrete wavelet transform (DWT); Image coding

1. Introduction

The main problem encountered in transmitting visual information over heterogeneous packet switched networks is the rapid degradation in the reconstructed image quality due to packet loss [1]. If packet retransmission is not guaranteed as opposed to the TCP protocol [1], then we should think of another appropriate mean to receive meaningful data despite the loss of packets. This problem finds its natural solution in the so-called multiple description framework [1]. Recently, multiple description coding (MDC) has taken considerable attention as a method of communication over unreliable packet switched networks. MDC is a technique which can be considered a joint source-channel coding (JSC) code for erasure channels [2]. It can efficiently combat packet loss without any retransmission, thus not only guarantee the real-time communication, but also relieve the network congestion. In the MDC scheme, several representations of the source, called descriptions, are generated. The descriptions are designed in such a way that the quality of the received signal degrades gracefully with the increase in the number of descriptions that are lost. Also, the descriptions are designed so that the quality of the reconstructed image is dependent only on the number of received descriptions and not on which descriptions are actually received.

One of the first MDC coder was designed by Vaishampayan [3] 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. Wang et al. [4–7] proposed applying a pairwise correlating transforms to introduce dependencies between two descriptions. Goyal et al. further generalized Wang's work to any number of descriptions, and coined the term generalized multiple description coding (GMDC) [2,8]. GMDC was later applied to image coding with correlating

* Corresponding author.
E-mail address: k_khelil@yahoo.fr (K. Khelil).

1434-8411/$ - see front matter © 2006 Elsevier GmbH. All rights reserved.
doi:10.1016/j.aeue.2006.07.003

transforms [8,9]. Servetto has designed and implemented error-resilient data compression algorithms based on the use of wavelets and MD scalar quantizers [10]. Pereira [11] and Sumohana [12] have studied MDC techniques based on wavelet transform, but not considering correlating transforms in wavelet domain.

In the first method proposed in [8,9], a vector of independent source samples (discrete cosine transform – (DCT) coefficients of the image) is transformed into another vector of correlated components. However, the redundancy introduced by the correlating transform will be assigned mostly to the DC coefficient. To alleviate this problem, the author assumes that the DC coefficient can be communicated reliably by some other means. As we will show later in this paper, the performance on real images of this technique is limited. The reconstruction image quality degrades significantly with the number of packet loss.

In this paper, we propose a new and simple MDC scheme based on the one described in [8,9] where we employ the discrete wavelet transform (DWT) instead of the DCT. Experimental results show that the proposed approach leads to a more graceful degradation of image quality with an increase in the loss in descriptions. Also with this technique, we do not need to consider reliable transmission of the DC components by other means.

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 and the simulation results obtained. Finally, a conclusion is presented in Section 4.

2. Multiple description transform coding (MDTC)

We propose to use the standard transform coding framework to realize the objective of MDTC. In conventional transform coding, the transform is used to decorrelate the input variables. Here, we use a transform to introduce a controlled amount of correlation among the transformed coefficients. In other words, a block of N independent, zero-mean variables with different variances is mapped to a block of N statistically correlated transform coefficients. The transform coefficients are distributed to different packets so that in the case of packet loss, the lost coefficients can be estimated from the received coefficients.

The case of two descriptions is depicted in Fig. 1 where the input source is encoded as *description*1 and *description*2. When only *description*1 or *description*2 is received, $\hat{x}^1$ or $\hat{x}^2$ can provide low but acceptable reconstructions quality at the receiver end. When both *description*1 and *description*2 are received, $\hat{x}^0$ provides better reconstruction.

Generally, the forward transform with quantization step-size Q of a source vector, whose components are assumed

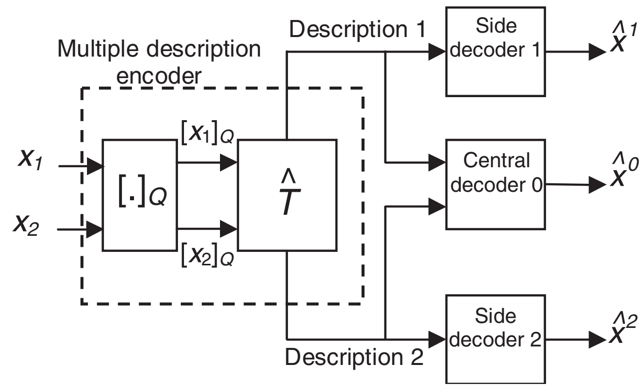

Fig. 1. Correlating transform structure for MD coding of a two-tuple source.

to be independent, zero-mean and Gaussian, is implemented as follows [8,9]:

(1) $[x_1 \ x_2 \ \cdots \ x_n]^t$ (t stands for transposition) is uniformly quantized: $x_q = [x]_Q$ with $[\cdot]$ denotes rounding.
(2) The quantized vector $[x_{q1} \ x_{q2} \ \cdots \ x_{qn}]^t$ is transformed with a discrete transform $\hat{T}$

$$y = \hat{T}(x_q). \tag{1}$$

(3) The components of y are independently coded.

Where $\hat{T}$ is a discrete version of a continuous transform T. The derivation of $\hat{T}$ from T is by first factoring T into a product of upper and lower triangular matrices with unit diagonals. The discrete version of the transform is then given by [8]

$$\hat{T}(x) = [T_1[T_2 \dots [T_q x_q]_Q]_Q]_Q. \tag{2}$$

When all the components of $y = [y_1 \ y_2 \ \cdots \ y_n]^t$ are received, the reconstruction is obtained from the inverse transform. The distortion is precisely the quantization error from step 1. If some components of y are lost, they are estimated from the received components using the statistical correlation introduced by the transform $\hat{T}$. Consider $k > 0$ components of y are erased, the reconstruction procedure is as follows [2,8].

Assume that $\tilde{y}_{\mathrm{r}} = [y_1 \ y_2 \ \cdots \ y_{n-k}]^t$ are received and $\tilde{y}_{\mathrm{nr}} = [y_{n-k+1} \ y_{n-k+2} \ \cdots \ y_n]^t$ are lost. The vector could be partitioned in “ received” and “ not received” components as $y = [\tilde{y}_{\mathrm{r}} \ \tilde{y}_{\mathrm{nr}}]^t$. The minimum mean square error (MSE) estimate of x given $\tilde{y}_{\mathrm{r}}$ is $E[x/\tilde{y}_{\mathrm{r}}]$.

Using the linearity of the expectation operator we have

$$\hat{x} = E[x/\tilde{y}_{\mathrm{r}}] = E[T^{-1}Tx/\tilde{y}_{\mathrm{r}}] = T^{-1}E[Tx/\tilde{y}_{\mathrm{r}}] \\ = T^{-1}E\left[\begin{bmatrix} \tilde{y}_{\mathrm{r}} \\ \tilde{y}_{\mathrm{nr}} \end{bmatrix} / \tilde{y}_{\mathrm{r}}\right] = T^{-1}\begin{bmatrix} \tilde{y}_{\mathrm{r}} \\ E[\tilde{y}_{\mathrm{nr}}/\tilde{y}_{\mathrm{r}}] \end{bmatrix}. \tag{3}$$

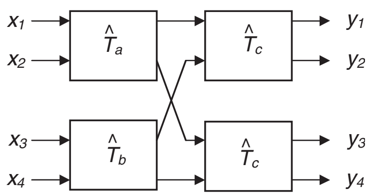

Fig. 2. Cascade structure for MDTC coding of four variables.

If the correlation matrix of y is partitioned in a way compatible with the partition of y as

$$R_y = T R_x T^{t} = \begin{bmatrix} R_1 & B \\ B^{t} & R_2 \end{bmatrix} \tag{4}$$

with R_x and R_y denote, respectively, the correlation matrices of the vectors x and y.

Then it can be shown that $\tilde{y}_{nr}/\tilde{y}_r$ is Gaussian with mean $B^t R_1^{-1} \tilde{y}_r$. Thus, $E[\tilde{y}_{nr}/\tilde{y}_r] = B^t R_1^{-1} \tilde{y}_r$ and

$$\hat{x} = T^{-1} \begin{bmatrix} \tilde{y}_r \\ B^t R_1^{-1} \tilde{y}_r \end{bmatrix}. \tag{5}$$

The optimal design of the transform $\hat{T}$ for Gaussian sources, where arbitrary (unequal, dependent) packet loss probabilities are allowed, is discussed in [8]. Here, we consider the simpler case where packet losses are independent and identically distributed (i.i.d.) and the transform is implemented as parallel and/or cascade combinations of 2×2 transforms.

It is shown in [4] that for coding a two component vector source, where each is likely to fail, it is sufficient to consider transforms of the form

$$T_a = \begin{bmatrix} a & 1/2a \\ -a & 1/2a \end{bmatrix}. \tag{6}$$

Such transforms give components with equal rate (or, equivalently, power) [2]. In the transform given by Eq. (6), a is a parameter determined from the redundancy introduced by the transform and the variances of the two components. This is used to build larger transforms as in Fig. 2 which illustrates the case of 4 components (descriptions) [8]. This is equivalent to the use of a transform of the form [8]

$$T = \begin{bmatrix} T_c & 0 \\ 0 & T_c \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} T_a & 0 \\ 0 & T_b \end{bmatrix}. \tag{7}$$

The coder implementation is completed by designing the transform T through numerical optimization of the parameters a, b and c given the total redundancy and the variances of the four components (descriptions). For more details, the reader is referred to [2].

For the coder of our application, the structure shown in Fig. 2 will be used in conjunction with wavelet transform to generate the descriptions.

3. Image coding using wavelet-based MDTC

The discussion before assures that random variables have Gaussian distribution, which is a base condition for using correlating transform. Theoretically, Mallat [13] has proved that the histograms of wavelet transform coefficients of natural images can be modeled by a family of Gaussian distribution. So we can use MDTC within wavelet domain on a strong basis.

The wavelets have often been employed in transform image coders. Although wavelets share many properties with the DCT (e.g. decorrelation), they also allow better localization in both frequency and space [14]. The DWT decomposes the original spatial-domain signal into various decomposition levels [15]. The decomposition levels comprise a number of subbands, each of them consists of coefficients that indicate the horizontal and vertical spatial frequency characteristics of the original samples. The first level decomposition, which will be used in our coder, includes four subbands, $LL1$, $HL1$, $LH1$ and $HH1$ [15].

We consider the case of four descriptions. This method is designed to operate on source vectors with uncorrelated components [8,9]. Such condition is obtained by forming vectors from DCT or DWT components. We refer to DCT-based coder used in [8,9] as MDTC/DCT coder.

The implementation of the MDTC/DCT coder proceeds in the following steps:

(1) The source image is transformed by an 8×8 DCT transformation.
(2) The DCT coefficients are uniformly quantized.
(3) The quantized DCT coefficients are split into 4 vectors.
(4) Correlating transform is applied to the 4 vectors, obtaining therefore the four descriptions.
(5) Entropy coding similar to that of JPEG is applied to each vector.

In step 3, the four vectors are formed from quantized DCT coefficients separated to the maximum in frequency and space with the DC coefficients assumed to be communicated reliably by some other means.

Our coding process based on DWT is implemented as follow

(1) The source image is transformed by the 1-level *biorthogonal* $B_{9/7}$ wavelet transform [16] obtaining therefore the four subbands: $LL1$, $HL1$, $LH1$, and $HH1$.
(2) The four vectors are formed: $\begin{cases} LL1 \to \textit{vector } 1 \\ HL1 \to \textit{vector } 2 \\ LH1 \to \textit{vector } 3 \\ HH1 \to \textit{vector } 4 \end{cases}$
(3) The DWT coefficients (the four vectors) are uniformly quantized.

Please cite this article as: Khaled Khelil et al., Multiple, description wavelet-based image coding using correlating transforms Int. J. Electron. Commun. (AEÜ) (2006), doi: 10.1016/j.aeue.2006.07.003

(4) Correlating transform, as described in Section 2, is applied to the 4 vectors, obtaining therefore the four descriptions.
(5) Entropy coding similar to that of JPEG is applied.

This technique is referred to as **MDTC/DWT**.

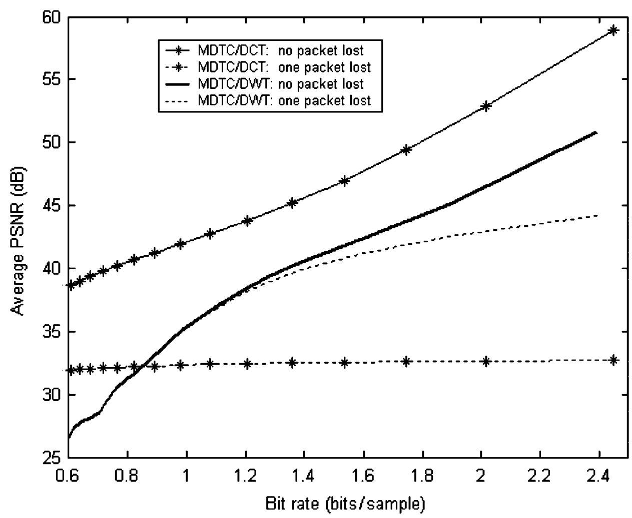

Fig. 3. Average PSNR versus bits per sample, ‘Lena’ image.

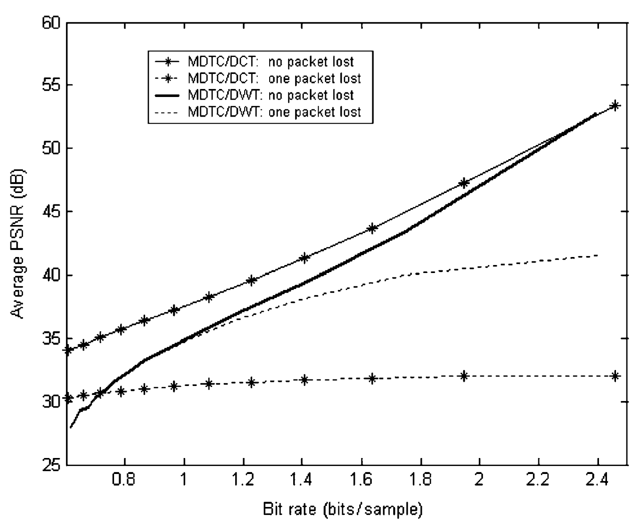

Fig. 4. Average PSNR versus bits per sample, ‘Goldhill’ image.

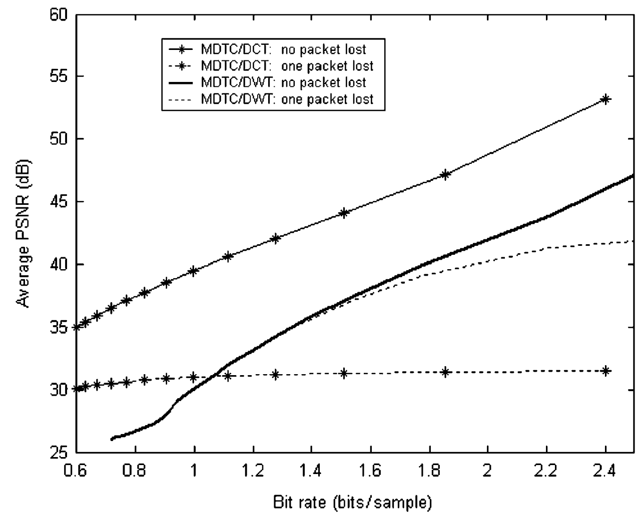

Fig. 5. Average PSNR versus bits per sample, ‘boat’ image.

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

Simulation results for the 512 × 512 ‘Lena’, 512 × 512 ‘Goldhill’ and 512 × 512 ‘Boat’ test images for the two coders are, respectively, given in Figs. 3–5.

In all figures, the average PSNR is reported as a function of the bit rate for the case of one packet dropped. We can observe that the MDTC/DWT performance increase rapidly with the bit rate and outperforms MDTC/DCT for higher bit rates, but the reconstruction quality of MDTC/DWT is worse than MDTC/DCT slightly at lower part of about 1 bit/sample.

To illustrate further the robustness of our approach for erasure channels, we have measured the PSNR of the restored images in the cases of 1, 2 and 3 packets dropped at a bit rate of 2 bits/sample. The corresponding results are reported in Table 1. We clearly see from the table that using MDTC/DWT results in an improvement in the reconstructed image quality when compared to MDTC/DCT.

For a qualitative comparison, the subjective qualities of Lena, Goldhill and boat images, for different levels of reconstruction with MDTC/DCT and MDTC/DWT coders are depicted in Figs. 6–11. In both cases, Figs. (a)–(d) illustrate respectively the situations of 0, 1, 2, and 3 packet loss. It is

Table 1. PSNR as a function of the number of packets lost for Lena, Goldhill and boat images

No. of packets lost	Lena image		Goldhill image		Boat image	
	MDTC/DCT PSNR (dB)	MDTC/DWT PSNR (dB)	MDTC/DCT PSNR (dB)	MDTC/DWT PSNR (dB)	MDTC/DCT PSNR (dB)	MDTC/DWT PSNR (dB)
0	52.89	46.88	48.34	46.80	49.30	41.98
1	32.65	43.12	31.97	40.86	31.45	40.41
2	27.62	36.12	27.35	30.34	26.06	33.20
3	25.82	32.67	25.28	28.12	23.71	28.48

Please cite this article as: Khaled Khelil et al., Multiple, description wavelet-based image coding using correlating transforms Int. J. Electron. Commun. (AEÜ) (2006), doi: 10.1016/j.aeue.2006.07.003

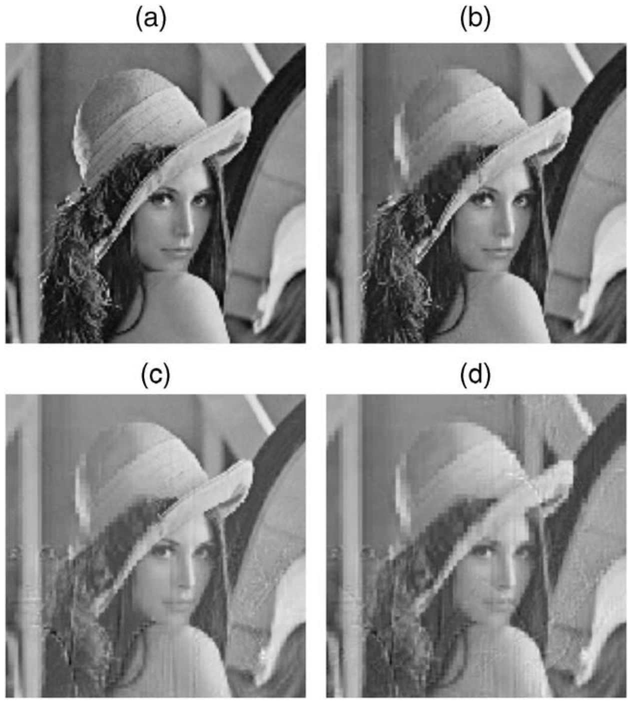

Fig. 6. Lena image reconstruction results for MDTC/DCT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 52.89 dB); (b) reconstructed image from 3 received packets (PSNR = 32.65 dB); (c) reconstructed image from 2 received packets (PSNR = 27.62 dB); (d) reconstructed image from 1 received packet (PSNR = 25.82 dB).

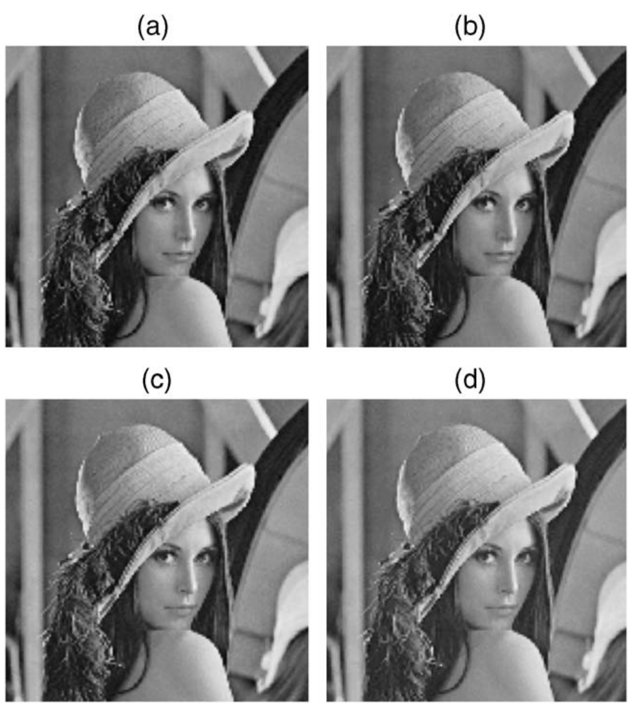

Fig. 7. Lena image reconstruction results for MDTC/DWT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 46.88 dB); (b) reconstructed image from 3 received packets (PSNR = 43.12 dB); (c) reconstructed image from 2 received packets (PSNR = 36.12 dB); (d) reconstructed image from 1 received packet (PSNR = 32.67 dB).

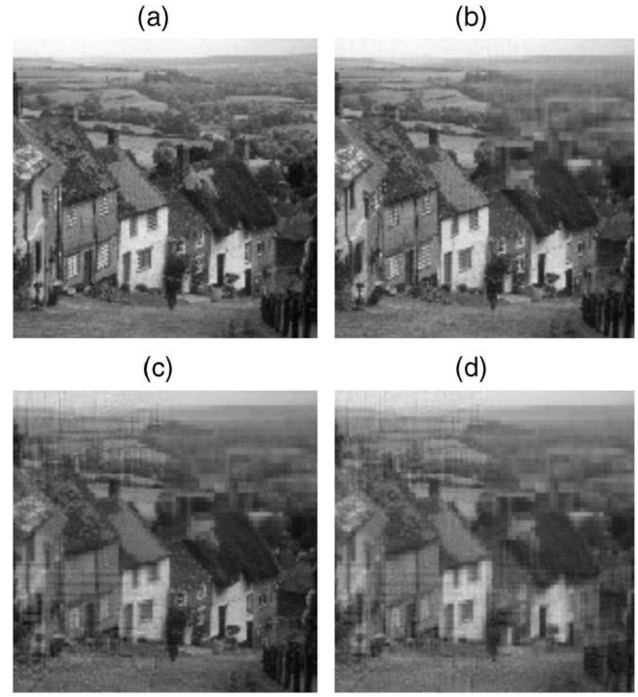

Fig. 8. Goldhill image reconstruction results for MDTC/DCT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 48.34 dB); (b) reconstructed image from 3 received packets (PSNR = 31.97 dB); (c) reconstructed image from 2 received packets (PSNR = 27.35 dB); (d) reconstructed image from 1 received packet (PSNR = 25.28 dB).

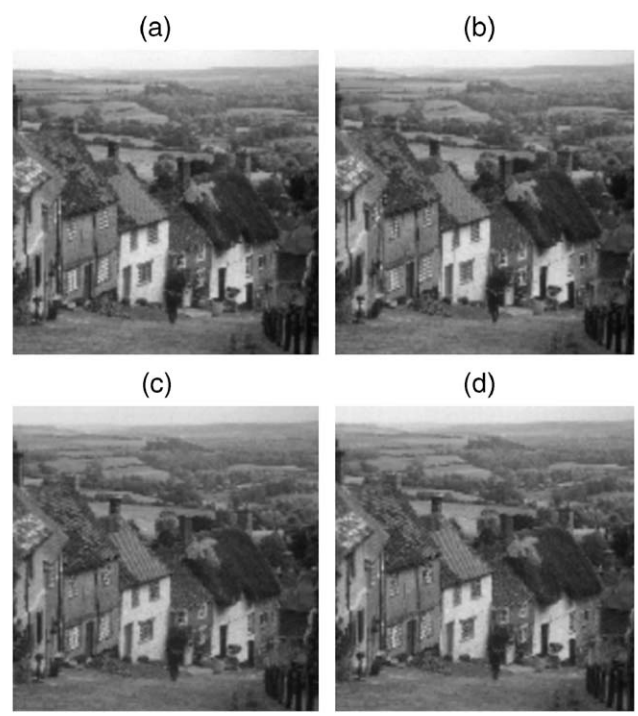

Fig. 9. Goldhill image reconstruction results for MDTC/DWT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 46.80 dB); (b) reconstructed image from 3 received packets (PSNR = 40.86 dB); (c) reconstructed image from 2 received packets (PSNR = 30.34 dB); (d) reconstructed image from 1 received packet (PSNR = 28.12 dB).

Please cite this article as: Khaled Khelil et al., Multiple, description wavelet-based image coding using correlating transforms Int. J. Electron. Commun. (AEÜ) (2006), doi: 10.1016/j.aeue.2006.07.003

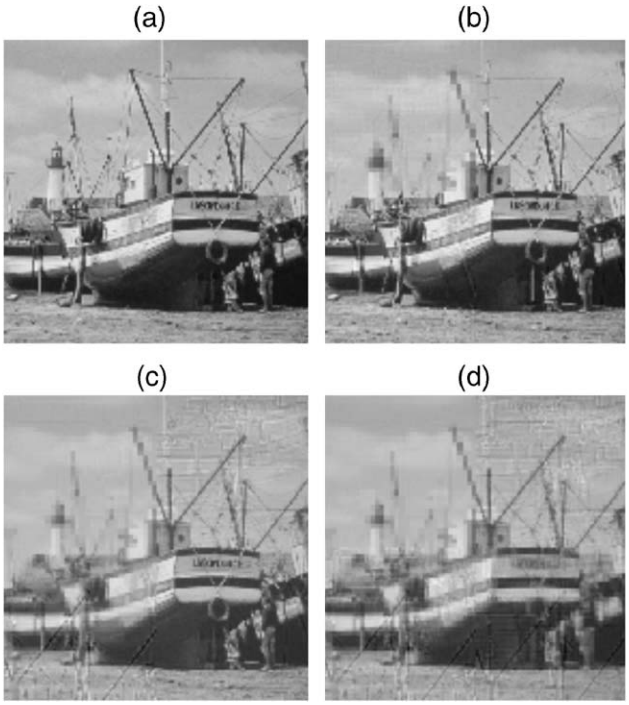

Fig. 10. Boat image reconstruction results for MDTC/DCT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 49.30 dB); (b) reconstructed image from 3 received packets (PSNR = 31.45 dB); (c) reconstructed image from 2 received packets (PSNR = 26.06 dB); (d) reconstructed image from 1 received packet (PSNR = 23.71 dB).

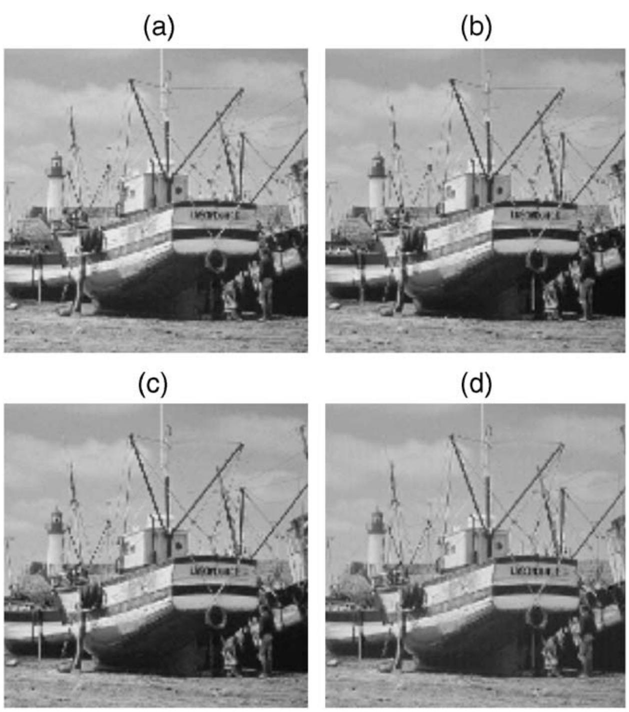

Fig. 11. Boat image reconstruction results for MDTC/DWT at 2 bits/sample: (a) reconstructed image from the 4 received packets (PSNR = 41.98 dB); (b) reconstructed image from 3 received packets (PSNR = 40.41 dB); (c) reconstructed image from 2 received packets (PSNR = 33.20 dB); (d) reconstructed image from 1 received packet (PSNR = 28.48 dB).

easily noticeable that for the wavelet transform based system, and even in the case of three packet loss, the system can still provide a better and more useful reconstruction of the original image (Figs. 7d, 9d, and 11d) compared to the DCT-based system (Figs. 6d, 8d, and 10d).

4. Conclusions

In this paper, we have considered a wavelet transform-based MDTC coder for coding still images for the case of four descriptions. We have carried out a comparative study of DCT- and DWT-based coding on Lena, Goldhill and boat test images. Our proposed approach shows to be more robust when transmitting images through unreliable networks. Through some experiments, we conclude that even if the wavelet-based MDTC system receives only one description (the three other descriptions being lost), it can still restore image with better reconstruction quality with respect to DCT-based MDTC system. Also, the same significant superiority in reconstruction quality applies if two descriptions are lost (and with a lower difference if only one is lost).

References

[1] Goyal VK. Multiple description coding: compression meets the network. IEEE Signal Process Mag 2001;18:74–93.
[2] Goyal VK, Kovacevic J. Optimal multiple description transform coding of gaussian vectors. IEEE data compression conference; 1998. p. 388–97.
[3] Vaishampayan V. Design of multiple description scalar quantizers. IEEE Trans Inf Theory 1993;39:821–34.
[4] Wang Y, Orchard M, Reibman A. Multiple description coding pairwise correlating transforms. IEEE Trans Image Process 2001;10:351–66.
[5] Wang Y, Orchard M, Reibman A. Multiple description image coding for noisy channels by pairing transform coefficient. IEEE first workshop MMSP97, Princeton, NJ, USA; 1997. p. 419–24.
[6] Wang Y, Orchard M, Reibman A. Optimal pairwise correlating transforms for multiple description coding. IEEE international conference on image processing ICIP98, Chicago, IL, USA; 1998.
[7] Orchard M, Wang Y, Vaishampayan V, Reibman A. Redundancy rate-distortion analysis of multiple description coding using pairwise correlating transforms. IEEE international conference on image proceedings; 1997. p. 608–11.
[8] Goyal VK, Kovacevic J. Generalized multiple description coding with correlating transforms. IEEE Trans Inf Theory 2001;47:2199–224.
[9] Goyal VK, Kovacevic J, Arean R, Vetterli M. Multiple description transform coding of images. International conference on image processing, Chicago, Illinois, USA; 1998. p. 674–8.
[10] Servetto S. Multiple description wavelet based image coding. IEEE Trans Image Process 2000;9:813–26.

[11] Pereira M, Antonini M, Barlaud M. Multiple description image and video coding for wireless channels. Session special EURASIP: Image Commun Special Issue Recent Adv Wireless Video 2003;18(10):925–45.
[12] Sumohana S, Channappayya JL, Robert WHJ, Bovik AC. Frame based multiple description image coding in the wavelet domain. International conference on image processing, Genova, Italy; 2005.
[13] Mallat S. A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans Pattern Anal Mach Intell 1989;11:674–93.
[14] Servetto S. Image coding based on a morphological representation of wavelet data. IEEE Trans Image Process 1999;8:1161–74.
[15] Christopoulos C, Skodras A, Ebrahimi T. The jpeg2000 still image coding system: an overview. IEEE Trans Consumer Electron 2000;46:1103–27.
[16] Daubechies I. Ten lectures on wavelets. CBMS conference, Lecture notes in series of applied mathematics, vol. 61. Philadelphia, PA: SIAM; 1992.

Khelil Khaled was born in Annaba, Algeria in 1970. He graduated from the National Institute of Electricity and Electronics (INELEC), Boumerdes, Algeria in 1993. He received his master degree from the Ferhat Abbes University, Setif, Algeria in 1996. He is preparing his doctoral thesis at the University of Setif, Algeria. His current research interests include multimedia signal processing, joint source-channel coding, multiple description coding and wavelets.

Raïs El Hadi Bekka was born in M'sila, Algeria. He graduated from the Ecole Polytechnique, Alger, 1980. He received his Doctorat d'Etat degree in Electonics Engineering from the University of Setif, Algeria, in 1994. Since May 2000, he has been Professor in the Department of Electronics, Engineering Faculty, University of Setif. His main research interests are in the areas of signal processing applied to biomedical signals and digital coding of waveforms.

Ali Djebbari was born in Sidi Lahcen (Sidi Bel Abbes), Algeria. He received his Dipl. El.-Ing. degree from USTO (ORAN, Algeria) in 1988, the Master degree from the Sidi Bel Abbes University in 1991, and the Doctorat es Science degree from the USTO (ORAN, Algeria) in 1997. Since 1991, he is in the Department of Electronics at the University of Sidi Bel Abbes. Currently, he is a Scientist Director of the Telecommunication and Digital Signal Processing Laboratory. His Research interests include wireless networks, signal processing for telecommunications, communication over multipath and fading channel, Orthogonal Multi-Carrier CDMA, Channel coding for telecommunications.

Jean Michel Rouvean was born in Maubeuge, France, in 1947. He received his Ph.D. degree in Electronics from the Universities of Paris VI and Valenciennes, France, in 1976. Currently, he is a Professor at the University of Valenciennes, France, where he teaches Electronics, Signal Processing and Telecommunications. Previously, he was involved in ultrasonics and acousto-optics. His current research interests is focused in: telecommunication systems and their application to security in intelligent transportation systems.

Please cite this article as: Khaled Khelil et al., Multiple, description wavelet-based image coding using correlating transforms Int. J. Electron. Commun. (AEÜ) (2006), doi: 10.1016/j.aeue.2006.07.003