EMBEDDED CROSS-DECODING SCHEME FOR MULTIPLE DESCRIPTION BASED DISTRIBUTED SOURCE CODING

Beerend Ceulemans, Shahid M. Satti, Nikos Deligiannis, Frederik Verbist, Adrian Munteanu

Department of Electronics and Informatics,
Vrije Universiteit Brussel
Pleinlaan 2, Brussels, Belgium

Department of Future Media and Imaging,
iMinds V. Z. W.
G. Crommenlaan 8, Ghent, Belgium

ABSTRACT

Using multiple description (MD) coding mechanisms, this paper proposes a novel coding framework for error-resilience in distributed source coding (DSC) in sensor networks. In particular, scalable source descriptions are first generated using a symmetric scalable MD scalar quantizer. These descriptions are then layered Wyner-Ziv (WZ) coded using low-density parity-check accumulate (LDPCA) -based syndrome binning. The decoder consists of two side decoders which attempt to iteratively decode their respective description at various LDPCA puncturing rates in the presence of a correlated side information. A central decoder exploits the inter-description correlation to further enhance the WZ rate-distortion performance when both descriptions are partially or fully received. In contrast to earlier work, our proposed decoding scheme also exploits the correlation that exists between bit-planes. Experimental simulations reveal that, for a Gaussian source, the proposed system yields a performance improvement of roughly 0.66 dB when compared to not exploiting inter-description correlations.

Index Terms— multiple description coding, distributed source coding, cross-decoding, layered Wyner-Ziv coding

1. INTRODUCTION

Modern day sensor networks consist of tiny low-power sensors deployed over a geographical area for monitoring physical phenomena, such as temperature, pressure, vibration or video-based surveillance of areas under observation. Communication in these networks is largely constrained by the low battery life of the employed lightweight sensors. Thus, low cost coding frameworks that can enable efficient compression and transmission of the sensed quantities are of key importance. Distributed source coding (DSC) [1, 2] aligns well with the needs of such sensor networks [3]. The sensors send their compressed output to a central station where joint decoding is performed, exploiting the inter-source correlations at the decoder side. An important application of DSC is distributed video coding (DVC) [4]. DVC is a particularly interesting video coding paradigm for lightweight devices that are limited in battery life, with applications in e.g., video surveillance, low complexity mobile video communication [4], wireless capsule endoscopy [5] and distributed coding of multi-view video [6].

In sensor networks, communication of data to a central station seldom occurs without losses, especially when transmission is carried out through wireless or best-effort networks. Multiple description (MD) coding [7] is an attractive solution in this respect as it ensures a gradual decrease in the source's reconstruction quality without the need for retransmission. In MD coding, instead of sending only one version of the source data, multiple mutually refinable source descriptions are sent over different physical or logical network paths. The source's reconstruction quality scales with the number of received descriptions, with highest quality attained when all descriptions are received. Multiple description scalar quantizers (MDSQs) [8] represent a common practical solution for MD coding; for other methods we refer to [7].

In this paper, we propose a novel MD based error-resilient coding framework for Wyner-Ziv (WZ) coding [2]. Coupling MD and WZ principles offers the possibility to maintain the lightweight encoding feature of WZ coding while making use of the error-resilient capabilities provided by MD coding. Earlier MD-WZ coding designs include the system of [9], employing the MD uniform scalar quantizers (MDUSQs) of [10] and layered WZ coding [11] via low-density parity-check accumulate (LDPCA) code syndrome binning. In this paper we propose a novel MD-WZ coding framework which improves over [9] in three ways. Firstly, the proposed system makes use of our recently proposed symmetric scalable MDSQ (SSMDSQ) instead of MDUSQ. SSMDSQs generate perfectly balanced descriptions and outperform the MDUSQ of [10] in conventional entropy-constrained coding [12]. Secondly, when both descriptions are partially or fully received, a novel cross-decoding mechanism is employed to significantly reduce the required bitrate compared to separately decoding the descriptions. In contrast to [9], our proposed cross-decoding exploits the correlation that exists between the coded bit-planes as well as the inter-description correlation. Thirdly, our design also employs a state-of-the-art

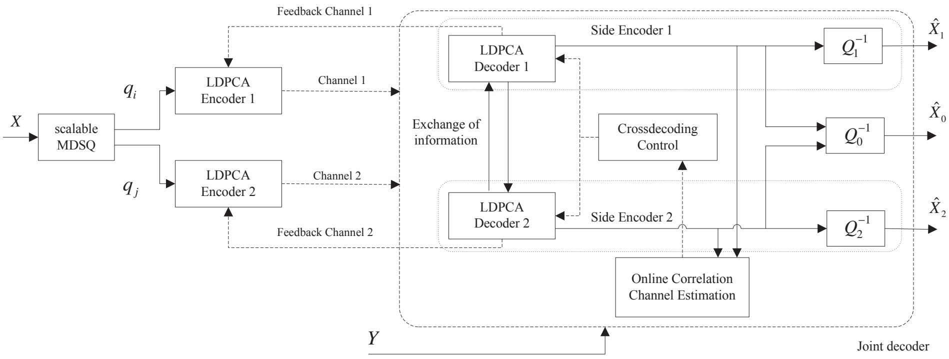

Fig. 1. High-level block diagram of the proposed MD-WZ coding system.

online correlation channel estimation (CCE) method [13].

The remainder of this paper is organized as follows: Section 2 presents the specifics of the proposed hybrid MD-WZ coding system. The proposed system is evaluated against a contemporary design in Section 3. Finally, Section 4 draws the conclusions of this work.

2. HYBRID MD-WZ CODING SYSTEM

Figure 1 illustrates the high-level block diagram of the proposed MD-WZ coding system. At the encoder, generated scalable descriptions are separately encoded using layered LDPCA-based WZ coding [11]. The decoder can decode these descriptions with the help of the SI either separately or jointly, using a cross-decoding mechanism. The separate decoding of descriptions can be directly inferred from [11]. The cross-decoding can exploit the inter-description correlation, which is presented next.

2.1. Inter-description correlation

The correlation between the descriptions comes from the index assignment (IA) based mapping in MDSQ [8]. In an embedded IA [10, 14, 15], side and central indices at different embedded levels can be created by grouping or by splitting the indices of a fixed-rate IA [12], resulting in scalable side and central quantizers.

Figure 2 shows an example of an embedded IA, where central indices $\{1, 2, ..., 19\}$ are mapped to a pair of side quantizers indices (q_i^p, q_j^p), where $p \in \{1, 2, \ldots, P\}$ denotes the refinement level and P is the number of bitplanes. Given that a source sample is quantized to a certain first side index q_i^p, we can derive some statistical information about its corresponding second side index q_j^p. Let $q_i^3 = 011$, then $q_j^3 \in \{010, 011, 100, 101\}$ (see figure 2). Roughly assuming a uniform input source distribution, one can say: $p(q_j^3 = 010 | q_i^3 = 011) = 1/4$, or conversely $p(q_i^3 = 011 | q_j^3 = 010) = 1/2$. This type of estimate can be computed for any p, leading to a quantitative measure of the correlation between the two descriptions at each quantization level.

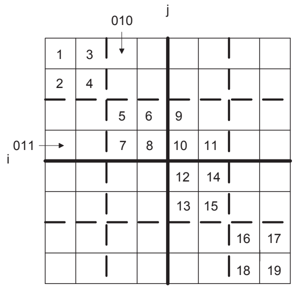

Fig. 2. An example of an embedded IA matrix for a scalable MDSQ. The different line styles correspond to the different quantization levels. The quantization indices are coded from left-to-right and top-to-bottom using the natural binary code.

2.2. Cross-decoding of two descriptions

Since the descriptions are scalable, transmission scenarios wherein descriptions are only partially received can occur. Thus, the joint decoding mechanism must exploit whatever correlation may exist between the received portions of the descriptions. For non-scalable systems, cross-decoding schemes for MDSQs [8] were first presented in [16, 17]. The work of [9] extends these earlier ideas to scalable coding frameworks using the MDUSQ of [10]. In this work we employ our recently proposed SSMDSQs [12], design a specific cross-decoding scheme for such quantizers and demonstrate that the proposed solution yields notable gains over [9].

Let $\mathbf{x}^n$ and $\mathbf{y}^n$ denote a block of n source samples and the receiver's SI, respectively. Let $\mathbf{u}_{(s)}^{r,n}$, $s = 1, 2$, denote two description of $\mathbf{x}^n$ coded at r bps (bits per sample) per channel. Starting from the most significant one, bit-planes of each description are separately WZ encoded using LDPCA syndrome binning. This results in two scalable bitstreams. At the receiver, two side decoders attempt to iteratively decode their respective bitstreams at the various puncturing rates of the employed LDPCA code using the SI. These decodings can occur either independently or, if both descriptions are received up to some refinement levels, jointly. The latter case is referred to as cross-decoding, wherein the two side decoders exchange information in order to exploit the inter-description correlation, described in Section 2.1. This results in a better rate-distortion (RD) performance compared to the independent decoding case.

When the estimates of the source bits of the first decoder converge, the resulting log-likelihood ratios (LLRs) at the variable nodes of the corresponding Tanner graph can be seen as *extrinsic* information that can be sent to the other side decoder as *a priori* information. Let $u_p^{(s)}$ be the bit in the p'th bit-plane for one particular sample x_k, with $k \in \{1, 2, \ldots, n\}$ and n being the block size. The decoder can determine the probability that the corresponding bit $u_p^{(1)}$ is either 0 or 1 as:

$$P\left(u_p^{(1)} = 0\right) = \frac{\exp\left(-L_k^{out,(1)}\right)}{1 + \exp\left(-L_k^{out,(1)}\right)} \quad (1)$$

$$P\left(u_p^{(1)} = 1\right) = \frac{\exp\left(L_k^{out,(1)}\right)}{1 + \exp\left(L_k^{out,(1)}\right)} \quad (2)$$

where $L_k^{out,(1)}$ are the LLRs at the variable nodes of the first decoder. From the IA matrix, we can directly compute the following conditional probabilities [9]:

$$P\left(u_p^{(2)} = c | u_p^{(1)} = 1\right) = \sum_{\substack{m: b_p(m)=1 \\ n: b_p(n)=c}} P(j = n | i = m) \quad (3)$$

$$P\left(u_p^{(2)} = c | u_p^{(1)} = 0\right) = \sum_{\substack{m: b_p(m)=0 \\ n: b_p(n)=c}} P(j = n | i = m) \quad (4)$$

where $m, n \in \{1, \ldots, M\}$, M is the alphabet size of the side indices (balanced case), and $b_p(l)$ is the p'th bit in binary representation of the quantizer index l. i and j are the row and column indices of the IA matrix for sides 1 and 2, respectively. Conditional probabilities in the IA matrix can be determined as explained in Section 2.1. If the source distribution is known, true conditional probabilities can be obtained. For example, in [18] the coding system is applied to wavelet transformed video frames, assuming Gaussian or Laplacian distributions depending on the subband to which a particular coefficient belongs.

Using equations (1-4) and the total probability theorem we can compute the *a priori* information for the second side decoder as:

$$L_k^{in,(2)} = \log \frac{P\left(u_p^{(2)} = 0\right)}{P\left(u_p^{(2)} = 1\right)} \quad (5)$$

The second side decoder adds this prior information to the LLRs obtained from the side information to compute the aggregate LLRs, i.e.,

$$L_k^{(2)} = \log \frac{P\left(u_p^{(2)} = 0 | y_k\right)}{P\left(u_p^{(2)} = 1 | y_k\right)} + L_k^{in,(2)} \quad (6)$$

2.3. Proposed cross-decoding scheme

Equations (3) and (4) only consider the bit-plane that is *currently* being decoded. Therefore, the lookup procedure (Section 2.1) in the IA matrix considers cells that may have already been ruled out by decoding previous bit-planes. In our proposed design, to which we refer as *embedded cross-decoding*, we perform an "embedded" lookup, hereby also considering all bit-planes that have already been successfully decoded. Formally, the summation in equations (3) and (4) is changed as follows:

$$P\left(u_p^{(2)} = c | u_p^{(1)} = 1\right) = \sum_{\substack{m: b_p(m)=1 \wedge \forall k<p: b_k(m)=u_k^{(1)} \\ n: b_p(n)=c \wedge \forall k<p: b_k(n)=u_k^{(2)}}} P(j = n | i = m) \quad (7)$$

$$P\left(u_p^{(2)} = c | u_p^{(1)} = 0\right) = \sum_{\substack{m: b_p(m)=0 \wedge \forall k<p: b_k(m)=u_k^{(1)} \\ n: b_p(n)=c \wedge \forall k<p: b_k(n)=u_k^{(2)}}} P(j = n | i = m) \quad (8)$$

Here, the summation indices cover the cells at the p'th bit-plane in the embedded IA matrix, but in contrast to equations (3) and (4) from [9], the summation only considers cells at levels $k < p$ that were decoded already and for which the value is therefore known. This reduces the uncertainty on the current bit-plane.

3. EXPERIMENTAL EVALUATION

The proposed system is evaluated on randomly generated data in the case when the source X and the SI Y are Gaussian random variables related via $X = Y + Z$, where Z is the correlation noise. The noise variance is estimated online using our recently proposed maximum likelihood estimation technique [13]. The employed LDPCA code works on blocks of 1584 samples quantized using 5 bit-planes at each side. The LDPCA decoder is limited to 100 iterations per puncturing rate. We report the bitrate and reconstruction quality per bit-plane, averaged out over 50 encoded blocks. The reconstruction quality is measured by the signal-to-noise ratio (SNR), computed as: $SNR = 10 \cdot log_{10}(\sigma_X^2 / E[(X - \hat{X})^2])$.

In Figure 3, the RD performance of the proposed embedded cross-decoding is compared to the regular cross-decoding method of [9] as well as to the separate decoding of both descriptions. In this experiment an SSMDSQ with 5 diagonals was employed. The figure shows that our proposed embedded cross-decoding scheme clearly outperforms the two others. By construction it is always at least as good as separate decoding, at the cost of increased complexity. The regular cross-decoding seems to bring little to no coding gains at all compared to separate decoding. The reason is that a uniform distribution in the embedded IA matrix is assumed instead of the actual source distribution to compute the conditional estimates $P(j|i)$. Similar to [18], it is expected that using the source pdf will lead to an additional coding gain for both regular and embedded cross-decoding.

Using the Bjontegard metric [19], we find that the proposed embedded cross-decoding scheme is on average 0.66 dB better compared to the separate decoding of the two descriptions. Similar results were observed in simulations with different system parameters - source distribution and variance, degree of inter-source correlation, number of quantization levels and block size.

Figure 4 depicts the RD comparison of the MDUSQ [10], employed in the approach of [9, 18], versus the SSMDSQ [12] when both are integrated in the proposed MD-WZ coding framework with embedded cross-decoding. The experimental setup is kept the same as in Figure 3. We find that for both the central and the Granular SNRs, the SSMDSQs exhibit a notable improvement in RD performance compared to MDUSQs.

Figure 5 reports the bitrate and average Granular SNR per bit-plane for different correlation-SNR (CSNR) values. The CSNR is a measure of the SI quality and is defined as: $CSNR = 10 \cdot log_{10}(\sigma_Y^2/\sigma_Z^2)$. Clearly, SSMDSQ saves considerable bitrate with respect to MDUSQ for roughly the same Granular SNR values.

4. CONCLUSIONS

This paper introduces a novel MD-WZ coding framework that is able to offer both the low complexity encoding and error-resilience properties that come from the DSC and MDC paradigms, respectively. In contrast to the state-of-the-art, the proposed embedded cross-decoding method exploits the knowledge of previously decoded bit-planes yielding a better RD performance. We have shown that, in our framework, SSMDSQs can achieve a better RD performance compared to MDUSQs. This is of particular significance when the packet-loss rate on the communication channels is not known and perfectly balanced descriptions are desired.

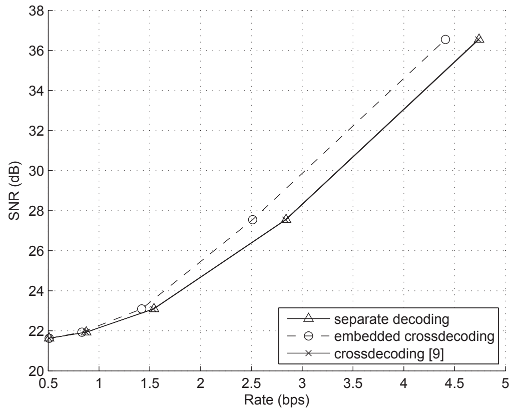

Fig. 3. Comparison of the different decoding schemes.

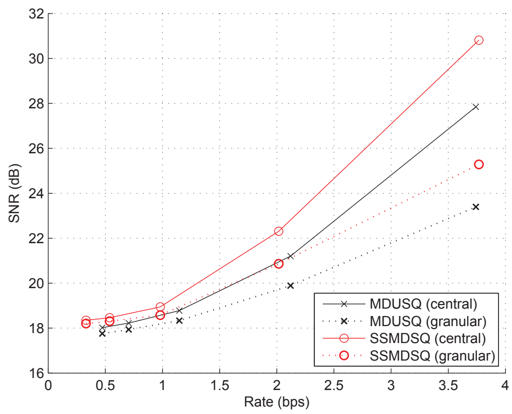

Fig. 4. RD comparison between MDUSQ and SSMDSQ. SNR of the central reconstruction and Granular SNR are plotted vs the total bitrate. The Granular SNR is computed as: $SNR_g = 10 \cdot log_{10}(\sigma_X^2/\sqrt{D_c D_s})$, with D_c and D_s being the central and average side MSE distortions, respectively.

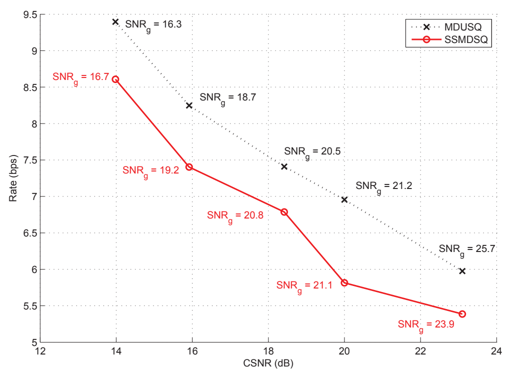

Fig. 5. CSNR vs rate plot, SNR_g values for each point are reported in dB.

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