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Multiple Description Lattice Vector Quantization with Joint Low Density Parity Check decoding and its application to Wireless Image Transmission

A thesis submitted to the in partial fulfillment of the requirements for the degree of Master in Electronics and Computer Engineering

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Abstract

Transmission of images over wireless channels is a difficult task due to the high probability of errors and the minimum tolerance to delays. In terms of source compression, the images were encoded using a wavelet based image encoding algorithm, motivated by the Set Partitioning in Hierarchical Trees (SPIHT) algorithm, the most efficient method for lossy image compression. In order to overcome the effects of transmission noise, we implemented a Source-Channel coding scheme exploiting Diversity, a technique used to increase the reliability of the wireless channels. Multiple description coding (MDC), the source coding scheme, is used to encode the source information into multiple streams, each independently decodable. So far, the MDC scheme has been mainly examined under the 'on-off' channel, for which each description is presumed to be either correctly received or not received at all. In order to efficiently protect the streams against real channel conditions, affecting the received packets with noise, we combined MDC with a forward error correction channel coding method, the low-density parity check codes (LDPC). The multiple streams are independently channel encoded and jointly decoded. We evaluated the proposed scheme's behavior using various channels (binary symmetric and Gaussian) and compared it to other MDC coding methods. The proposed scheme shows promising results in combating the channel noise even in low bitrates.

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1 Introduction

Transmission of images and video over Internet and wireless communication channels requires robust and efficient source and channel coding algorithms. The current image coding standard JPEG2000 as well as the Set Partitioning in Hierarchical Trees (SPIHT) algorithm, provide progressive image compression, where the original image can be reconstructed incrementally. The main drawback to progressive organization of the bitstream is that it is highly prone to transmission noise. This makes channel codes necessary, so as the source encoded bitstreams to be protected. Traditionally, the problems of source coding and channel coding have been addressed independently. However, when the constraints of the communication channel are considered, a joint source/channel coding scheme (JSCC) is found to be the most promising choise for the transmission of images over noisy channels.

In [1.1], Draper et al. outline the characteristics of video transmission over wireless channels as a conjunction of issues concerning the qualities of both the video streaming and the wireless channels. The sensitivity to errors and time varying characteristics, along with the sensitivity to delay and packet loss, make the optimization of the transmission a difficult task. In that sense, wireless channels have characteristics that must be taken into account in order for reliable transmission of the video streams to be achieved. One of those qualities being diversity. Diversity is based on the fact that individual channels experience different levels of fading and interference. So, various diversity methods are used to improve the reliability of communication as in the case where multiple versions of the same signal may be transmitted and/or received and combined at the receiver. Diversity can be archived in time, frequency, antenna and path.

Frequency diversity, antenna diversity, and path diversity provide significant performance benefits with limited latency penalties. Furthermore, time diversity and path diversity can be implemented at the application layer, which allows them to be more efficiently coupled with specialized source coding. Consequently, path diversity secures the most efficient combination of diversity optimized source coding and low latency.

Source-Channel coding [1.2], where source and channel coding are performed at the application and the physical layer respectively, increase the quality of the received video, taking diversity into consideration. There are three types of source and channel diversity schemes, as shown in figure 1

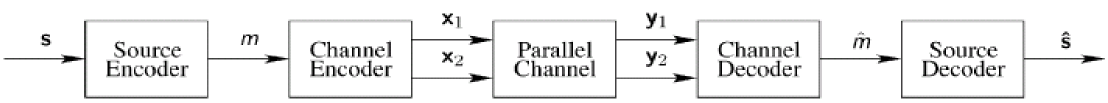

Illustration 1: Single source - Multiple channel coding

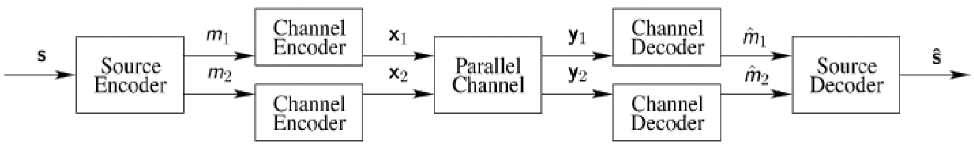

Illustration 2: Multiple source - Single channel coding

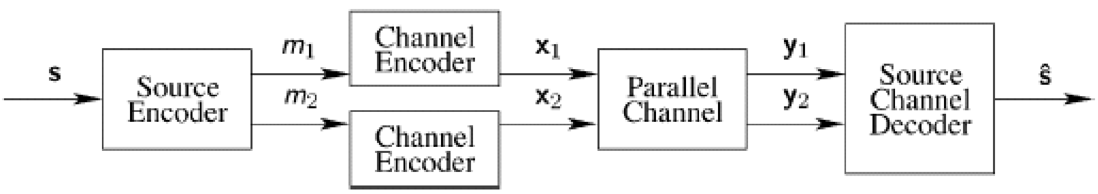

Illustration 3: Multiple source - Single Channel - Joint Source Channel Decoding

In the first case, showing in figure 1, the source is encoded using a source encoder, and two codes are generated by the channel coder at the transmitter. After the transmission over the parallel channel, the channel decoder takes the two codes and produces a single source code that is sent to the source decoder. In the second case, presented in figure 2, two different codes are produced by the source encoder, and each one is independently encoded by the channel encoder and then sent over the parallel channel. In the third case, the ones used in the proposed method , illustrated in figure 3, the source encoder again produces two codes from a single source and each code is independently encoded by the channel encoder. The difference lies in the fact that after transmission the received codes are jointly decoded at the source-channel decoder and the original source signal is estimated.

As pointed out in [1.2], the best source-channel coding architectures are still unknown, and this is why this issue remains a highly active research area. Yet, the authors note that path diversity and multiple description coding can be further improved by combining the two with some form of error correction coding.

The main objective of this thesis is to examine the transmission of multiple description video streams encoded with the SPIHT motivated algorithm over wireless erasure channels, using error correcting codes. Multiple description coding has been mainly examined using the "on-off" channel, a simple model for describing erasures channel, in which case each packet is either correctly received or not received at all. This model, though simple, does not reflect the real channel. In real wireless channels, we assume that the received packets are affected by transmission noise resulting is alternation of the received bitstreams and packets. In order to shield the multiple description coding for noise, we propose the addition of an error correcting code. Low density parity check codes, have been exonerated as one the most efficient method of error correction, showing performance near to Shannon's channel capacity theorem. Nevertheless, simple protecting each stream with low density parity check codes, would affect the needs for transmission bandwidth and would not be an efficient method for protecting the description, since the reason for having multiple description is in fact, error protection. Following that observation, an a recent paper showing how to apply low-density parity check codes on correlated sources, we developed a source-channel decoding method for the efficient protection of multiple description coding of zerotrees of wavelet coefficients. We tested the proposed scheme over various channel conditions such as binary symmetric and Gaussian channels and compared it in terms of reconstructed image quality to state-of-the-art video transmission schemes.

The thesis outline is the following: In chapter 2 we present the existing technology in image compression and transmission. In chapter 3, we present the underlying technologies in image compression, image transmission and error correcting codes. In chapter 4, we present the proposed image encoding framework, whereas in chapter 5, we present the experimental results and comparisons with other image coding schemes. We conclude the thesis and present the further work in chapter 6.

2 Existing Methods

In general, practical systems of image compression are based on first applying a decorrelating transform, then performing scalar quantization and finally performing entropy coding of the quantized coefficients [2.1].

Image coding algorithms used for the source decorrelation can be roughly divided into two categories; the ones based on Discrete Cosine Transform and the ones based on Discrete Wavelet Transform. JPEG is a well known standard for lossy image compression based on Discrete Cosine Transform, whereas JPEG2000 and Set Partitioning in Hierarchical Trees (SPIHT) [2.2] are the Discrete Wavelet Transform based counterparts.

Discrete Cosine Transform (DCT) is a block-based transform, usually applied to 8x8 pixel blocks. The attribute that establishes DCT as the most successful transform is compactness. By compactness, we mean that most of the signal's energy is compacted to the lower frequency coefficients, while most of the higher frequency coefficients are small or zero after quantization, and small or zero-valued coefficients tend to be clustered together. In practice, only a few coefficients are necessary for a coarse approximation of the image, making it suitable for low-bitrate communication.

In contrast Discrete Wavelet Transform (DWT) is applied to the entire image and not to separate blocks. DWT can be implemented by a cascade of low-pass and high-pass filters, a filter bank. At each stage the image is decomposed into horizontal (H), vertical (V), diagonal (D), and baseband (B) subband images, each being one-fourth the size of the original image. Similar to the DCT, most of the signal's energy is concentrated into the lower-frequency subbands and most of the high-frequency coefficients are set to zero.

The DWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using a high-pass filter *h*. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other in a form known as quadrature mirror filter. Then the outputs of the filters are downsampled by 2 following Nyquist sampling theorem.

$$y_{\mathrm{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

$$y_{\mathrm{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input, so the frequency resolution is doubled. The structure of the filter analysis is shown in figure 4.

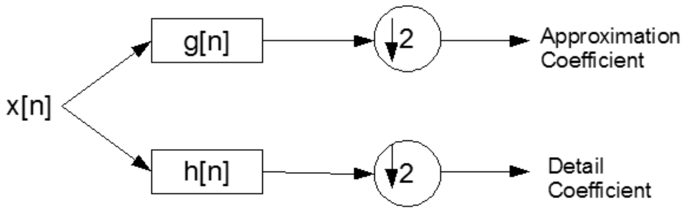

Illustration 4: Block Diagram of analysis filter

The most significant advantage of DWT versus DCT in terms of image transmission is that DWT embedded coding allows for progressive reconstruction of the image using partial bitstream information.

On the other hand, a significant disadvantage of DWT versus DCT is the computational complexity. Traditional DCT encoding of images is perform on 8x8 bock sizes, minimizing the complexity and space requirements, whereas DWT is apply at once on the full image. Working through this problem, the authors in [2.5], developed a fast method for image encoding called *lifting scheme.* The in-place computation of of coefficients had a major impact on memory and processing power required. The gain on the processing power in lifting scheme is go great that the JPEG2000 standard is only provided in terms of lifting coefficients. In the initialization phase of the algorithm a 'lazy' wavelet transform is applied by splitting the original signal into odd $\{d^j_0\}$ and even $\{s^i_0\}$ coefficients, as show in figure 5.

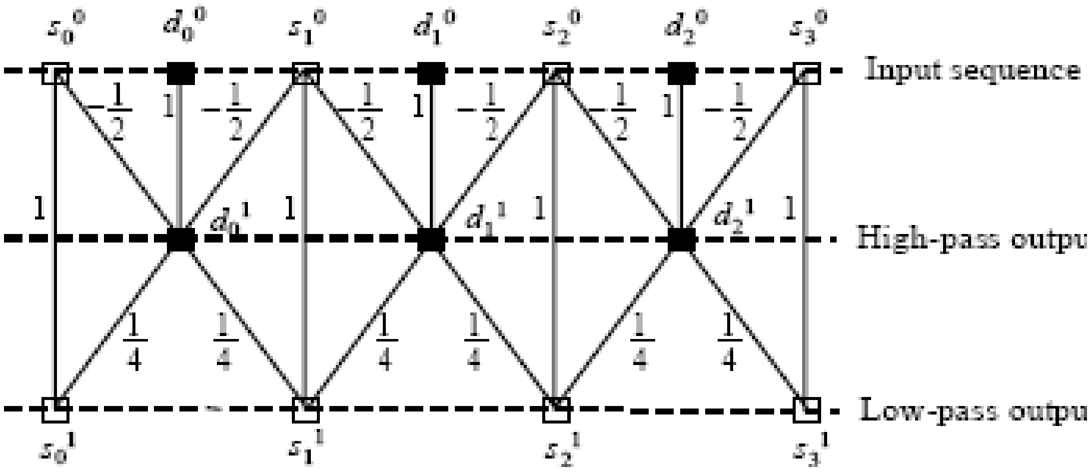

Illustration 5: Block Diagram of analysis filter

The algorithm runs in two steps that are repeated, the prediction and the update. At the prediction step consist of applying linear operation on the odd samples and generating the prediction error vector {d1j}. In the case of the (5,3) filter-bank the prediction error is evaluating using the following equation:

di1=di0-1/2(si0+si+10).

The resulting coefficients are the high-pass coefficients. In the update step the low-pass coefficient are evaluating in a similar manner. In the case of the (5,3) filter-bank, the coefficients are generating following equation

s1i=s0i+1/4(di-11+di1).

The update and prediction steps are iterated, with different weights at each iteration.

Along with the development of efficient encoding algorithms, DWT has gain much attention. It has been applied in the JPEG2000 standard and two very effecting image compression algorithms, the Embedded Zerotree of Wavelets (EZW) [2.6], and Set Partitioning is Hierarchical Trees (SPIHT) [2.7]. The last two algorithms have demonstrated increased compression efficiency, generation of fully embedded codes, progressive transmission, low complexity and fast encoding/decoding algorithms.

Moving from image to video coding, a key technology is the predictive coding. In predictive coding coefficients can be encoded according to already coded adjacent coefficients or event from previous frames, the so-called motion compensation, in which cases more than one frames need to be stored. Predictive coding is suitable for both lossy and lossless coding.

The most successful video encoder based on DCT are the MPEG-1 and the MPEG-2. In MPEG[2.3], each video sequence is divided into one or more groups of pictures (GOPs). There are four types of pictures: I-, P-, B-, and D-pictures. Each GOP is composed of one or more pictures, one of which must be an I-picture. I-pictures (Intra-coded pictures) are coded independently with no reference to other pictures and provide random access points in the compressed video data. I-pictures use only transform coding without motion compensated predictive coding, so they provide only moderate compression.

P-pictures (Predictive-coded pictures) are coded using the forward motion-compensated prediction from the preceding I- or P-picture. P-pictures provide more compression than the I-pictures and they also serve as references for B-pictures and future P-pictures.

B-pictures (Bi-directional-coded pictures) allow macroblocks to be coded using bi-directional motion-compensated prediction from both the past and future reference I- or P-pictures. In the B-pictures, each bi-directional motion compensated macroblock can have two motion vectors: a forward and a backward motion vector which references to a best matching block in the previous or next I- or P-picture. The motion compensated prediction can be formed by the average of the two referenced motion compensated blocks. B-pictures provide the best compression compared to I- and P-pictures.

D-pictures (DC-pictures) are low-resolution pictures obtained by decoding only the DC coefficient of the Discrete Cosine Transform coefficients of each macroblock. D pictures are rarely used, but are defined to allow fast searches on sequential digital storage media.

The typical MPEG-1 input format has a 352x240 resolution for NTSC systems (30 frames/s) and a 352x288 resolution for PAL systems (25 frames/s).

Since the formulation of wavelet coded is a new idea developed by a Belgian mathematician Ingrid Daubechies in 1988 [2.3], the is a small number of video encoders available. One such coder is the 3D-SPIHT[22.4], the video extension of SPIHT. The SPIHT algorithm, which has proved so successful in still image coding, is also shown to be quite effective in video coding, while retaining its attributes of complete embeddedness and scalability by fidelity and resolution. Three-dimensional spatio-temporal orientation trees coupled with powerful SPIHT sorting and refinement renders 3D SPIHT video coder so efficient that it provides performance superior to that of MPEG-2 and comparable to that of H.263 with minimal system complexity. Extension to color-embedded video coding is accomplished without explicit bit-allocation, and can be used for any color plane representation. In addition to being rate scalable, the proposed video coder allows multiresolution scalability in encoding and decoding in both time and space from one bit-stream.

These attributes of scalability, lacking in MPEG-2 and H.263, along with many desirable features, such as full embedded-ness for progressive transmission, precise rate control for constant bit-rate (CBR) traffic, and low-complexity for possible software-only video applications, makes the proposed video coder an attractive candidate for for multi-media applications. Moreover, the codec is fast and efficient from low to high rates, obviating the need for a different standard for each rate range.

Besides image and video encoding a lot of work has been done on the application layer of the OSI model. The most notable is the Real-Time Transport Protocol (RTP) [2.8] developed by the Audio-Video Transport Working Group of the IETF and first published in 1996 as RFC 1889 which was made obsolete in 2003. RTP provides end-to-end network transport functions suitable for applications transmitting real-time data, such as audio, video or simulation data, over multicast or unicast network services. RTP does not address resource reservation and does not guarantee quality-of- service for real-time services. The data transport is augmented by a control protocol (RTCP) to allow monitoring of the data delivery in a manner scalable to large multicast networks, and to provide minimal control and identification functionality. The functionality offered by RTP includes resequencing if needed, loss detection for quality estimation and recovery, intra-media synchronization which includes removing delay jitter through playout buffer, drifting sampling clocks, inter-media synchronization such as lip sync between audio and video, quality-of-service feedback and rate adaptation and source identification.

3 Underlying Technologies

Wavelet-based image compression

In terms of image compression the current state-of-the-art image coders are based on the wavelet transform. Wavelet decompositions naturally represent image data in a hierarchical manner. Consequently, wavelet decompositions are suitable for progressive image compression. The resulting wavelet coefficients are grouped into approximation and detail coefficient subbands. Approximation coefficient subbands, calculated at each level of the filter bank structure, provide a low resolution approximation of the original image being represented. As the number of levels increases, this sub-band becomes increasingly coarse. The detail coefficient subbands provide details corresponding to the difference in information contents between the adjacent approximations levels. As the number of levels increases, these details become increasingly coarse. Each detail subband contains wavelet coefficients that represent high-frequency components prominent in horizontal, vertical and diagonal spatial orientations. This means that lower-frequency, less-detailed information is contained in the first transform level, while more-detailed, higher-frequency information is contained in further transform levels. As an example, the wavelet transform of the standard 'Lenna' image is shown in Figure 3. For simplicity, only two levels of the transform are shown here. The first transform level results in subbands LH1, HH1, HL1, and LL1. Only sub-band LL1 is passed on for further wavelet decomposition, generating the next transform level and creating subbands LH2, HH2, HL2, and LL2.

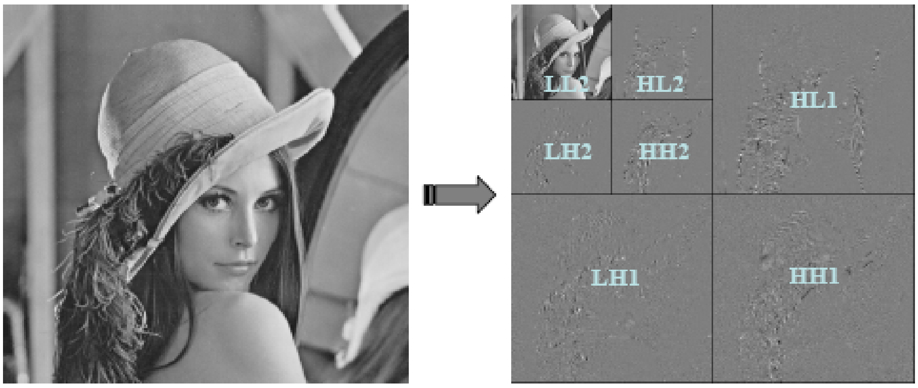

Illustration 6: Wavelet subband decomposition of Lenna

Two well known algorithms that utilize the wavelet decomposition into subbands are the Embedded Zerotrees of Wavelet (EZW), developed by Shapiro et al. [3.1] and The set partitioning in hierarchical trees (SPIHT), developed by Said et al. [3.2].

The basic SPIHT algorithm, as it has been presented by Said and Pearlman makes intensive use of dynamic data structures to exploit the self similarities. The parent-child relations of the wavelet coefficients are shown in Figure 7. In order to exploit the self-similarities during the coding process, oriented trees of four offspring are used for the representation of a wavelet transformed image. Each node of the trees represents a coefficient of the transformed image. The levels of the trees consist of coefficients at the same scale. The trees are rooted at the highest scale of the representation. The SPIHT algorithm assumes that each coefficient a_{ij} is a good predictor of the coefficients which are represented by the subtree rooted by a_{ij}. The overall procedure is controlled by an attribute, which gives information on the significance of the coefficients. More formally, a coefficient is insignificant with respect to a threshold t if its magnitude is smaller than 2t. Otherwise it is called significant with respect to the threshold t.

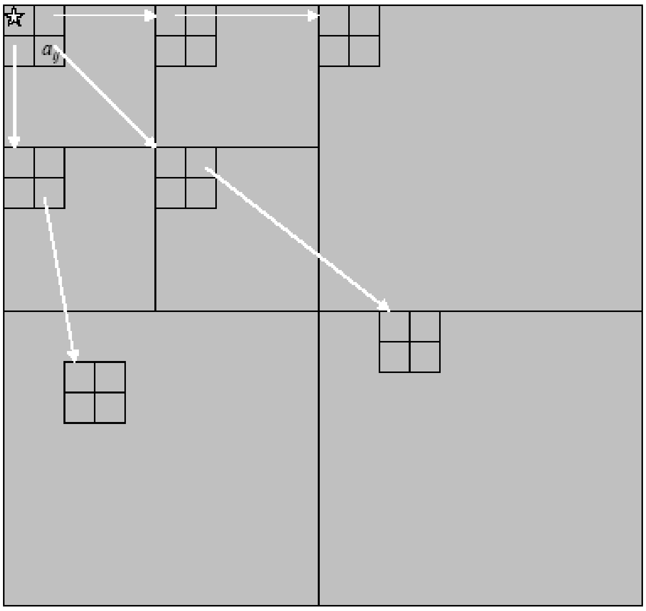

Illustration 7: Zerotrees formulation order

In the SPIHT algorithms, the coefficients of a wavelet transformed image are classified into three sets, namely the list of insignificant pixels (LIP), which contains the coordinates of those coefficients that are insignificant with respect to the current threshold t , the list of significant pixels (LSP), which contains the coordinates of those coefficients which are significant with respect to t, and the list of insignificant sets (LIS), which contains the coordinates of the roots of insignificant subtrees. During the compression procedure, the sets of coefficients in LIS are refined and if coefficients become significant they are moved from LIP to LSP. The bitstream can thus be progressively organized. The final step of SPIHT is entropy encoding of the resulting bitstream. We did not perform entropy encoding because the generated bitsreams are pass through a vector quantizer and forward error correction.

3.2. Multiple Description Coding

An application layer source coding scheme that offers robust behavior in the presence of transmission errors is Multiple Description Coding (MDC) [3.3]. The basic idea of multiple description coding is to encode the information source into M descriptions, which are sent separately over M different channels. Each channel is assumed to have independent probability of failure, therefore any subset of the descriptions may get lost. The decoder will make the best possible decoding of the arrived descriptions.

In the classic formulation of the MDC, the goal is to create two (or more) descriptions of input signal under the following three conditions:

Condition 1: $D_0 < D_{central,min}$

Condition 2: $R_1 = R_2 > R_{min}$

Condition 3: $D_1 = D_2 < D_{side,min}$

where $D_{central,min}$ is the minimum acceptable distortion at the receiver when both descriptions are received,D_1 and D_2 are the distortions when only the one description is received, R_1 and R_2 are the achievable transmission rates of each channel and $D_{side,min}$ are the minimum acceptable distortions when only one channel is working.

In the balanced case, where all descriptions are equally important, every description should contain enough information of the source so that reasonable decoding quality can be expected with only one single description. When more descriptions are available, each description should be able to provide additional information so that the decoding quality can be improved.

The intuition for designing a multiple description coder is to make each description individually good, and different from the others.

Individually, optimal descriptions have rates close to the classical rate-distortion bound, which is the minimum amount of mutual information needed to describe the source for certain distortion. In practice, all the optimal descriptions have much similar information, which suggests that the combination of the descriptions does not provide much quality gain. To improve this, each of the descriptions must contain different information of the source, which means that individual descriptions can't be optimal. This is the dilemma in the design of multiple description coding.

A terminology often seen in the multiple description coding community is index assignment. In the quantizer based multiple description coding, the source is first quantized with a conventional near-optimal quantizer, and each quantization cell is assigned to M indices, where each index is transmitted over one channel. Each index should be able to decode to a reconstruction point close to the cell, and the combination of indices should exactly identify the cell. This problem is referred to as the multiple description index assignment problem. The same theory is extended to lattice quantization.

The MDC philosophy has been implemented in a number of ways such as scalar based quantization [3.4], forward error correction [3.5], pairwise correlating transform [3.6], frame based encoding [3.7], domain based [3.8] and lattice vector quantization [3.9].

MDC coding for image transmission has been implemented in a number of ways. In [3.4], Vaishampayan et al. showed a systematic way to construct a resolution constrained (fixed rate) multiple description scalar quantizer (MDSQ) with two descriptions. The encoder can be decomposed into two steps, a conventional scalar quantizer plus an index assignment function. An example of a multiple description scalar quantizer is presented in figure 8

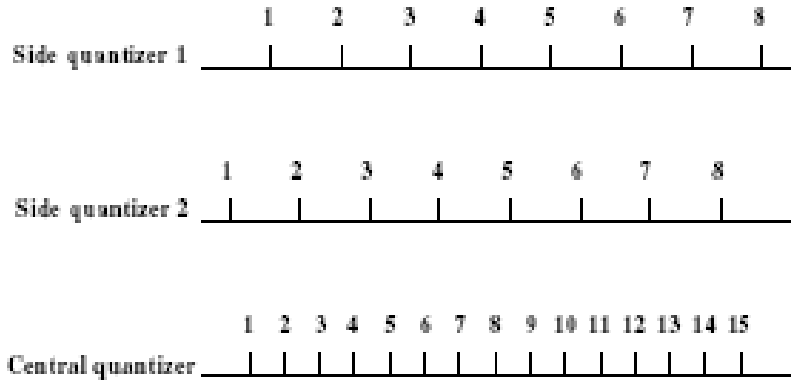

Illustration 8: Multiple Desciprion Scalar Quantization

The conventional quantizer partitions the real line into quantization cells, and the index assignment function produces a pair of indices for each quantization cell. The index assignment function must be invertible such that the central decoder can correctly produce the original index for each pair of given indices.

The optimization of the index assignment function is difficult to solve, and Vaishampayan developed several heuristic solutions that were shown to be close to optimal. The design of the index assignment function in MDSQ can be visualized in an index assignment matrix, where each item in the matrix maps to a pair of indices. Given all possible pairs of indices, the goal in MDSQ design is to find a scanning sequence of the index assignment matrix that gives a selection of index pairs that minimizes the spread of each side quantization cell. The matrix is filled only on the main diagonal, from upper-left to lower-right. Figure X show an example of the index assignment.

	000	001	010	011	100	101	110	11 1
000	1							
001	2	3						
010		4	5					
011			6	7				
100				8	9			
101					10	11		
110						12	13	
111							14	15

The outputs from the MDSQ encoder can be further encoded using a variable length code to achieve improvement performance. The extension is very similar to the extension done in the entropy constrained Lloyd algorithm. Using the fixed index assignment function from MDSQ, the necessary conditions for optimal ECMDSQ quantizer are formulated as a Lagrange functional that minimize the central distortion subject to constraints on side distortions and entropies of the descriptions. An iterative training algorithm is used to find a locally optimal entropy constrained quantizer.

In [3.5], Yao Wang et al. proposed the use of pairwise correlating transform in order to generate multiple descriptions. Their idea is on the other side of traditional signal transform coding, where the goal is to produce uncorrelated coefficients, since the statistical dependency of the correlation cannot be exploited. In the case of MDC coding, the statistical dependency between coefficients from different descriptions could be utilized in order to estimate coefficients that are lost during transmission. As an example, consider two quantized random variables X1 and X2; the resulting transformed coefficients as evaluate as $Y_1=2(-1/2)(X_1+X_2)$ and

$Y_2=2(-1/2)(X_1-X_2)$, with a correlation $(\sigma_{12}+\sigma_{22})-(\sigma_{12}-\sigma_{22})$.

In [3.6], Goyal, V.K et al. Used overcomplete expansions of the original signal to generate multiple descriptions. This multiple description generating framework is based on describing a N-dimensional vector with a M-dimensional vector, where M>N by multiplying the N-dimensional vector with an orthogonal basis of a higher order M-dimensional space. A classic example, given by the authors, is a 3x2 orthogonal basis

$$\begin{vmatrix} y_1 \\ y_2 \\ y_3 \end{vmatrix} = \begin{vmatrix} 1 & 0 \\ -1/2 & -\sqrt{3}/2 \\ -1/2 & \sqrt{3}/2 \end{vmatrix} \begin{vmatrix} x_1 \\ x_2 \end{vmatrix}$$

In order for the transform to be revisable, the orthogonal basis should be a frame. A set of vector $\Phi=\{\varphi_i\}$, is called a frame if

$$0 < A\|x\|^2 \leqslant \sum \|\langle \varphi_i, x\rangle\|^2 < B\|x\|^2 < +\infty$$

for all $x \neq 0$. A and B are called frame bounds and they represent a metric of the redundancy of the frame.

The redundancy of the frame expansion has a direct impact on the resiliency to channel errors. Later, Channappayya et al. [3.10] examined the application of frame expansions to multiple description of wavelet coefficients. In their work, the zerotrees, that were generated after the 2D discrete wavelet transform, were rearranged as Nx1 vectors and multiplied by a MxN frame operator, resulting in a Mx1 vector, where M/N is the redundancy introduced with the frame expansion.

In [3.8], Bajic et al. proposed a domain-based multiple description coding for images and video. The key idea, is the partitioning of the transform domain into sets that are maximally separated. In the case of image, the disjoint sets are created by partitioning the 2D lattice. This idea has been extended to multiple description lattice vector quantization

In multiple description lattice vector quantization, the source signal is quantized using different vector quantizers for each channel. As a result we have a coarse representation of the original signal when a single channel is working and finer representations when more channels work. Moving from the one-dimensional scalar quantizer to multi-dimensional space of vector quantizers closed the gap between the two channel distortion and the rate-distortion bound. More specifically for an infinite size quantizer, the normalized second moment of inertial, a measure of the space filling ability of shape, is $2\pi e^{-1}$, while for the scalar quantizer is 1/12. The difference in space filling ability has a direct impact on the quantization error.

This method is known as lattice vector quantization. Servetto et al. in [3.9] first suggested the use of MDC wavelet based Image Coding. Recently, H. Bai et al. [3.10] applied this scheme to zerotrees produced through the dyadic decomposition of the source image, using wavelet transform, aiming at high compression of the video, with minimum visual distortion.

3.3. Error Correcting Codes

Multiple Description Coding has been mainly examined under the Gilbert (“on-off”) channel model, where each description's packets are either correctly received or not received at all. Yet, this model fails to represent the real channel condition. Recently, there has been work in studying the behaviour of MDC under noisy channel model, where noise affects the transmitted packets.

The most efficient error correcting algorithms nowadays are the Turbo and ow Density Parity Check codes. Turbo codes where developed by Berrou, Glavieux, and Thitimajshima [3.11] and are generally concatenated codes that involve concatenation codes via a random interleaver and an iterative maximum-a-posteriori decoder. The design is based on the an the use of a pseudo-random interleaver which makes the code appear random and an iterative decoding algorithm between the two concatenated codes in order to approach the channel capacity.

There is also work on the use of error correcting codes combined with multiple description, such as in [3.12], where concatenated codes (RCPC and CRC) were used and in [3.13], where the multiple descriptions are turbo coded and transmitted over multiple antennas. In [3.14], the authors proposed an image transmission scheme for wireless communications using Turbo and Reed-Solomon (RS) codes for unequal error protection. The scheme is based on the SPIHT for source compression and an unequal error protection algorithm is used of the formulation of constant size channel blocks allowing efficient decoding. In [3.15], the authors proposed an extension to the previous algorithm by using a Lagrangian optimization for the combination of the packet size, the interleaver and the channel coding rate, in order to improve the performance of the source coding scheme. In [3.16], irregular repeat accumulate (IRA), a subcategory of LDPC codes were employed to combat erasures in scalable transmission of JPEG2000 bitstreams over binary symmetric channels.

Low density parity check codes (LDPC) were developed by Gallager in 1962 [3.11] but were not given much attention due to the overwhelming complexity compared to the existing hardware. They were rediscovered by MacKay and Neal [3.17,3.18]. Today they represent the most efficient method for forward error correction since they approach the maximum channel capacity set by the Shannon Limit. LDPC codes are used for error protection of video sources in the new standard for satellite communications, the DVB-S2 [3.19] and are approved for deep-space communication by Nasa [3.20].

LDPC codes are linear block codes obtained from sparse bipartite graphs (called Tanner graphs). Suppose that G is a graph with n left nodes (called message or bit nodes) and r right nodes (called check nodes). The graph gives rise to a linear code of block length n and dimension at least n-r in the following way: The n coordinates of the codewords are associated with the n message nodes. The codewords are those vectors $(c_1, \ldots, c_n)$ such that for all check nodes the sum of the neighbouring positions among the message nodes is zero. In this work the codes are represented by binary streams. Figure 9 illustrates an example of the Tanner graph.

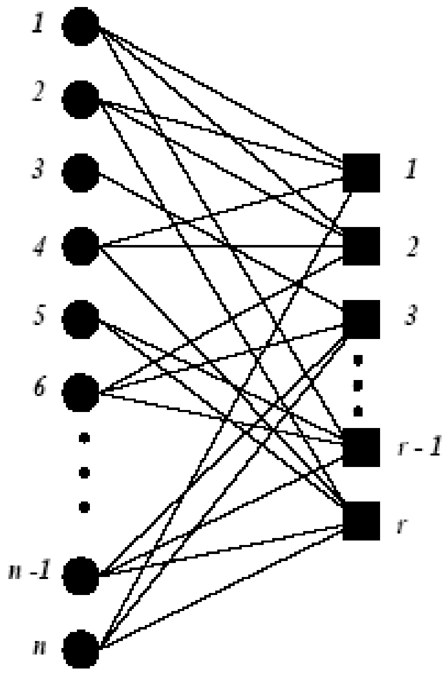

Illustration 9: Bitparite graph (Tanner graph)

The graph representation is analogous to a matrix representation by looking at the adjacency matrix of the graph: let H be a binary $r \times n$ matrix in which the entry $(i; j)$ is 1 if and only if the ith check node is connected to the jth message node in the graph. Then the LDPC code defined by the graph is the set of vectors $c = (c_1, \ldots, c_n)$ such that $H \cdot c^T = 0$. The matrix H is called a parity check matrix for the code. Conversely, any binary $r \times n$ matrix gives rise to a bipartite graph between n message and r check nodes, and the code defined as the null space of H is precisely the code associated to this graph. Therefore, any linear code has a representation as a code associated to a bipartite graph (note that this graph is not uniquely defined by the code). However, not every binary linear code has a representation by a sparse bipartite graph. If it does, then the code is called a low-density parity-check (LDPC) code. The sparsity of the graph structure is the key property that allows for efficient decoding of LDPC codes using iterative decoding algorithm.

A Tanner graph of LDPC codes is called regular if every message node is connected to equal number of check nodes and every check node is connected to equal number of message nodes. Otherwise, the LDPC codes are called irregular.

Similar to turbo codes, LDPC codes with iterative decoding provide very good performance over a variety of channels with reasonably low complexity. In particular, irregular LDPC codes [3.21] are known to outperform regular codes and turbo codes and to approach the capacity of several channels at large block lengths. Moreover, compared to turbo Codes, LDPC codes exhibit several other advantages [3.22]: i) Iterative decoding algorithms for LDPC codes are parallelizable and can be realized at much faster speed than turbo decoders, and ii) almost all the errors are detectable. The only drawback of LDPC codes is its encoding complexity. The encoding complexity of LDPC codes is in general quadratic in n.

LDPC codes are linear codes that use a sparse parity matrix and a belief propagation algorithm in order to detect transmission errors. In our case LDPC codes are used for protection of the descriptions generate by a multiple description lattice vector quantizer when transmitting over multiple binary symmetric channels, a subcategory of a multi-input multi-output (MIMO) channel. The use of LDPC in MIMO channel was examined in [3.23].

In [3.24], the authors proposed a multiple description LDPC coding scheme in order to combat the problem of predictive mismatch. The systems utilizes the MD scalar quantizer to produce LDPC codes that are used as side information in a Wyner-Zin decoder of an H.263 video encoder

LDPC has been used as part of a joint source channel coding scheme for the protection of JPEG2000 streams over uncorrelated flat fading channels, where sum-product LDPC codes are used for error correction in [3.25]. In the proposed algorithm, the LDPC feds back log-likelihood ratio (LLR) to increase the reliability of the source decoding. Finally, in [3.26], the authors proposed iterative decoding of differentially space-time coded multiple descriptions of images.

Both turbo and LDPC codes exhibit near channel capacity performance and have efficient and computational reasonable constructing algorithms. However, the design of LDPC codes is more flexible that Turbo, allowing for faster, easier and more precise design. The drawback is that generally turbo codes preform better in smaller block size.

4 Proposed Methodology

Motivation

Wireless channels are prone to errors. An image/video transmission coding algorithm must be able to handle those errors and display a robust behavior. The multiple description framework represents a reliable mechanism for combating the transmission errors. It does so by generating multiple descriptions of the same source information and transmitting them over distinct channels. In terms of wireless communication, multiple description takes advantage of the source coding diversity. Multiple description coding has been mainly examined under the "on-off" channel model, where a transmitted packet will arrive either intact or not at all. This model does not represent the reality of wireless transmission. What actually happens is that all packets are received, but they are affected by noise. In this scenario, we cannot distinguish which packet is correct and which is not. Following that observation, we are forced to add some kind of error control. Recently rediscovered low density parity check codes are channel codes that approach the theoretical limit in point-to-point communication. In the proposed method, different descriptions generated by a multiple description encoder, are further protected with low-density parity check codes.

Furthermore, in recent literature, it has been proposed that combining diversity in source and channel coding could offer even greater quality in the presence of transmission errors. Under that assumption, we optimized the proposed scheme by jointly decoding the low-density parity check codes of each description. In the work of Daneshgaran et al [4.1], the authors concluded that the empirical cross-correlation between two sequences is robust to channel errors. The empirical cross-correlation is

simply the XOR addition of the binary streams representing the two sources. Applying the iterative decoding of correlated source to descriptions generated by MDC is straightforward. In addition to the decoding of the LDPC codes of the correlated, an extra step has been added at the end, where the resulting indexes of the descriptions are cross-checked in order to establish a valid index pair.
The proposed scheme is presented in figure 10

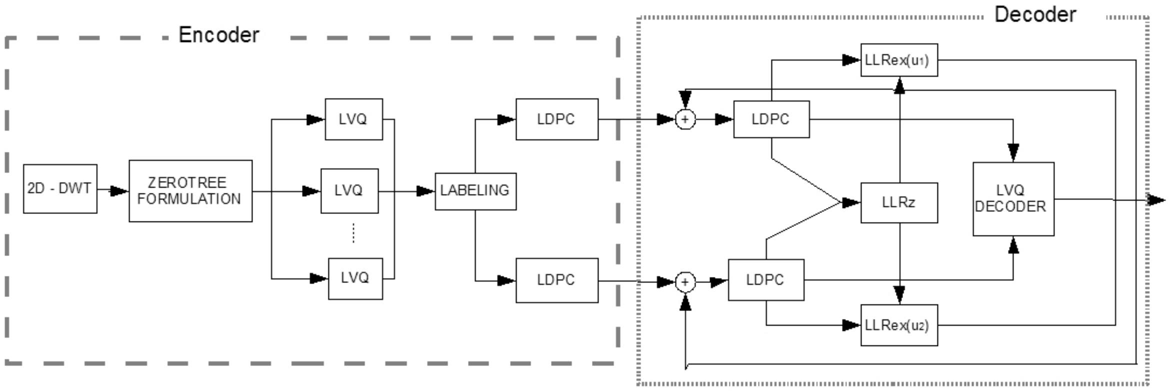

Illustration 10: Block diagram of the proposed scheme

There are two main parts, the encoder and the decoder. The encoder is realized with five components, the wavelet transform (2D-DWT), the zerotree formulation, the lattice vector quantization (LVQ), the labeling function and the low-density parity check encoding (LDPC). On the other side of the transmission is the decoder. The decoder consists of three components, the low-density parity check decoder (LDPC), the log-likelihood estimation (LLRex(u1),LLRex(u2) and LLRz) and the lattice vector decoder (LVQ). Each component will be further described in the following sections.

4.1 Lattice Vector Quantization

A lattice is define as a regular arrangement of point in a Euclidean space. Let $a_1...a_n$ be a set of linearly independent vectors of m-dimensional Euclidean space R^m, with m>n. The set of all vectors $\Lambda=\{ x : x = u_1a_1 +...+ u_na_n \}$, with $u_1..u_n$ integers is called a n-dimensional lattice. A lattice can also be constructed using the generating matrix G: $\Lambda=\{ x : x = uG \}$. Figure 11, show two lattices the Z_2 and the A_2, the dots represent the lattice points and the edge the corresponding Voronoi cells.

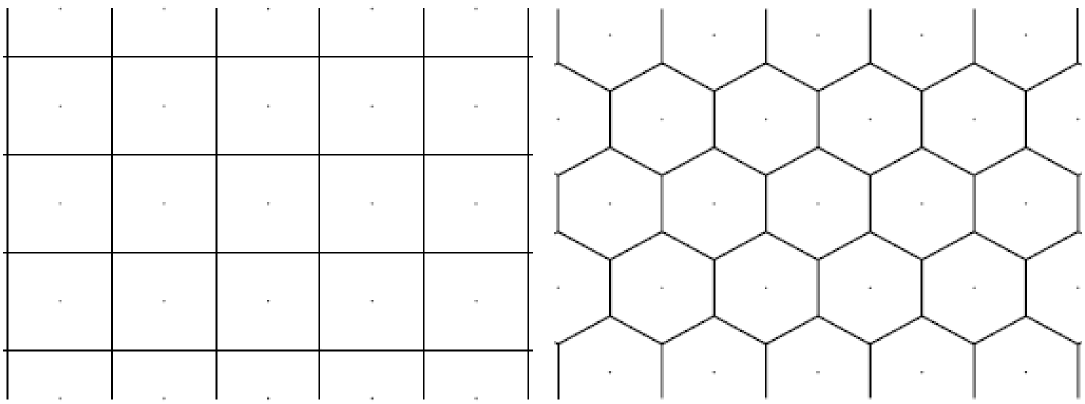

Illustration 11: Examples of A2 and Z2 lattices

A geometrically similar sublattice Λ' can be generated from a lattice Λ by multiplying the lattice with an orthogonal matrix : $\Lambda'=c\Lambda U$, where c is a constant scalar and *U* is an orthogonal matrix. This implys that a geometrically similar sublattice can be generated by scaling and rotating the original lattice.

The multiple Description lattice vector quantizer (MDLVQ) can be defined as a triplet Q(Λ, Λ' , ℓ), where Λ is a lattice, Λ' is a geometrically similar lattice to Λ and ℓ is the indexing function. Using ℓ, each point $\lambda \varepsilon \Lambda$ gets mapped to a pair $(\lambda'_{red}, \lambda'_{green})$ that uniquely identify λ. ℓ is referred as the vector index assignment and N=[Λ/Λ'] is defined as the reuse index and serves as an indicator of the redundancy of the quantizer. A larger N results in smaller central distortion.

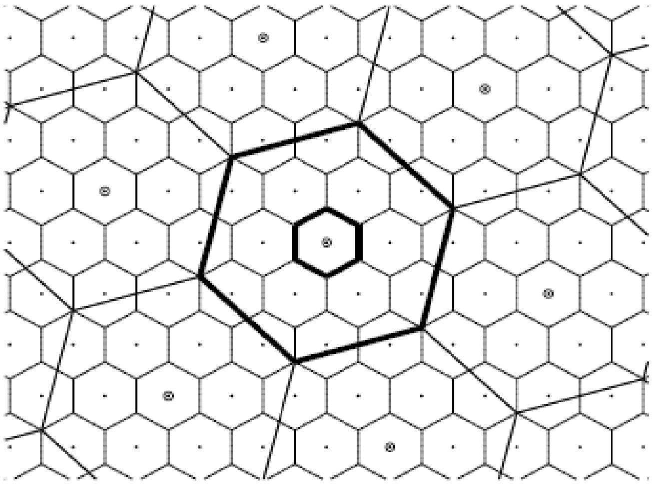

Illustration 12: Example of lattice to Sublattice geometry

The algorithm used for the construction of the lattice vector quantizer, named SVS after the authors of the original paper, is described in [4.2] and is briefly presented here. At the encoder of a MDLVQ system the source vector **x** is quantized to the closest vector λ in the lattice Λ, which is denoted λ=Q(**x**). The labeling function ℓ maps the vector λ to a pair (λ'_{red}, λ'_{green}) so that $l(\lambda)=(\lambda'_{red}, \lambda'_{green})$. At the decoder the reverse function l' is used to reconstruct the original point λ.
Figure 13, presents an example with reuse index N=7

Lattice point	Label
a	(O,A)
b	(O,B)
c	(O,C)
d	(O,D)
e	(O,E)
f	(O,F)

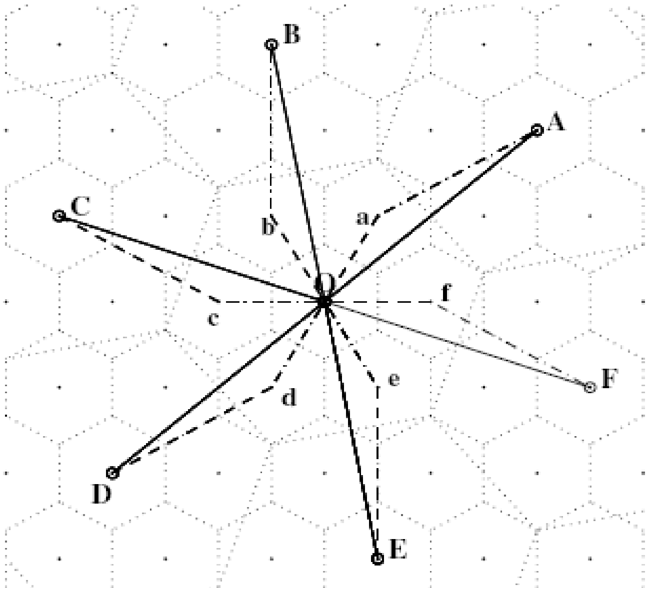

Illustration 13: Example of N=7 multiple desciprion lattice quantization

For the general case of Gaussian source with a total rate $R_{md}/2$ per channel the rate distortion function for the MDC scheme is defined [4.3] by

$$R_{\mathrm{md}}(D_0, D_1) = \frac{1}{L}\log\frac{1}{D_0} + \frac{1}{L}\log\frac{(1-D_0)^2}{(1-D_0)^2-(1-2\mathrm{D}_1+D_0)^2} \qquad (1).$$

and the average per- channel distortion is given by

$$\bar{d}_0 = \sum_{\lambda\in\Lambda}\int_{v(\lambda)} \|x-\lambda\|^2 P_L(x)\,dx \qquad (2).$$

Assuming that each Voronoi region is small, the distortion, in terms of the normalized second moment G(Λ), is defined as

$$\bar{d}_0 \approx G(\Lambda)\, v^{2/L}$$

and the two channel distortion is given by

$$\bar{d}_s \equiv (\bar{d}_1 + \bar{d}_2)/2$$

4.2 Wavelet transform and Zerotrees formulation

The image is decomposed into subbands using a 2D DWT. After transforming the image into wavelet coefficients, we employ the hierarchical set partitioning algorithm for the formulation of the zerotrees. The choice of zerotrees is based on the robustness to transmission errors in a two-fold way. First, the distribution of the wavelet coefficients should be made in such a way that the loss of a packet in the LL subband will not result in a catastrophic error and second, grouping the coefficients appropriately can exploit intra-vector redundancy well.

Using an embedded zerotree formulation algorithm we create zerotrees for every coefficient in the low-low (LL) subband. Each LL coefficient has tree children in the high-low (HL), low-high (LH) and high-high (HH) subbands.

4.3 Lattice Vector Quantization of coefficients.

Pairs of zerotree coefficients are grouped into vector that are fed into the Lattice Vector Quantization module. The LVQ is based on the A2 lattice, which is equivalent or similar to the hexagonal lattice. In order to create the lattice, we use the generation matrix G as in [4.3],

$$G = \begin{bmatrix} 1 & 0 \\ \frac{-1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix}$$

By taking pairs of zerotree coefficients from each M x 1 vector as 2 dimensional vectors, each pair produces a quantized field λ. At the encoder of an MDLVQ system, the source vector x is quantized to the nearest vector λ in a lattice Λ. The quantizer mapping is denoted by

λ=Q(x). The labeling function ℓ is used to map the sublattice Λ', that is geometrically similar to Λ, so that each lattice point λ in Λ gets mapped by ℓ to a pair of sublattice points (λ'red, λ'green) that uniquely identifie λ. The mapping is done in a way such that

$$\Lambda \rightarrow \ell(\Lambda) \subset \Lambda' \times \Lambda'$$

The index of sublattice point λ'red is transmitted over one channel and index of λ'green is transmitted over the other. The amount of redundancy that is inserted by the lattice vector quantization is controlled by a the reuse index N

4.4 Selection of Scaling and Sublattice Index

In [4.4], Goyal et al. assert that *generally it is the low indexes that are important.* This assumption is verified by their experimental results, showing that for reuse index N=13 the central and side distortions differ by 16.8 db. When the channel statistics are known the average total distortion can be expressed as:

$D=p_oD_o+p_1(D_1+D_2)$ (3).

where $p_o=(1-p)/(1+p)$ is the probability of receiving both description and $p_1=(p)/(1+p)$ is the probability of receiving only one description

A key point in the optimization process is the increase in the encoder's complexity In the A2 lattice, the search is performed between 13 possibilities in a simple way, where further improvement can be expected by using the symmetries of the system.

When p=0, the encoder is the same as the encoder in [4.3] and the partitioning is done into the lattice Voronoi cells. As p increases the sublattice points get bigger Voronoi cells until p=1, when the encoder uses the sublattice points for the quantization. This optimization procedure improves the convex hull of operating points of the vector quantizer. In turn, knowledge of the channel characteristics can improve the reliability of the transmission mechanism in the presence of errors.

4.5 LDPC encoding

The use of LDPC codes over correlated source is mainly based on the work of Deneshgaran et al .[4.1]. In their work they define the empirical cross-correlation as follows:

Let X and Y be two binary correlated vectors of length L. Z is defined as the XOR addition of the two vector Z=X (+) Y. Let the number of non-zero elements of Z be a. The empirical cross-correlation is defined as p=a/L. Deneshgaran et al established in that work that p is a robust indicator of the correlation when transmitting over a binary symmetric channel, even in the case of crossover probability as high as 0.2.

Each description generated by the MD Lattice Vector Quantizer is independently encoded by a LDPC encoder and transmitted over a binary channel subject to additive white Gaussian noise. LDPC are linear codes with a space parity check matrix of the form $H_{(N-K)xN}$,where N is the size of the codeword and K is the information bit stream size. The design of the space parity matrix is a key component of the design. In our case, we have used the parity matrices proposed in the DVB-S2 standard [4.5]. The parity check matrices of the DVB-S2 standard are irregular and structured in order to reduce the storage requirements, so that a sub-matrix has a lower triangular form, thus avoiding the need for the construction of their generator matrices. Following the standard, the parity check matrix has the form $H_{(N-K)xN} = [A_{(N-K)xK}\ B_{(N-K)x(N-K)}]$ where B is a staircase lower triangular matrix. Imposing this structure to the parity check matrix has a minor effect in performance (within 0.1 db).Each generated codeword has the form $u=[c,p_u]$, where u is the systematic part and p_u is the parity part.

4.6 Joint source channel decoding. (LDPC decoding)

Assume that a pair of lattice indexes l_1 and l_2 are generated by the MD lattice vector quantizer. Each index is transmitted through a noisy binary channel. In the uncoded case, where each index is binary encoded without any variable coding, the channel erasures will cause a number of bits to change. The joint LDPC decoding of the indexes will minimize the number of altered bits by co-evaluating the value of each bit. In order to further increase the robustness of the proposed method an index validation method is added after the joint LDPC decoding.

At the receiver the bit streams are jointly decoded in an iterative fashion through global and local iterations. At each global iteration an estimation of the source correlation is obtained and passed to the sum-product decoder, which performs local iterations. The joint decoding scheme is presented in figure X. The LDPC decoder is based on the belief-propagation algorithm and works on soft information quantized on 3 bits.

Assume that x is the transmitted binary phase shift keying (BPSK) symbol and y is the noisy received signal so that

y=x+n, where n is a Gaussian random variable with zero mean representing the noise. If x=+1 when transmitting bit 0 and x=-1 when transmitting bit 1, the a priori log likelihood ratio (LLR) for the transmitted bit is

$$LLR(x)=\log\frac{(p(x=+1|y))}{(p(x=-1|y))} \qquad (4).$$

The sign of the LLR determines the symbol and the magnitude offers an indication for the reliability of the decision.

At the decoder the two received sequences r_1 and r_2 are used to estimate the a posteriori probabilities of the symbols for the initialization phase of the LDPC decoders as expressed in equation 5.

$$LLR(r_{j,i}) = \log \frac{P(x_{j,i}=1 | r_{j,i})}{P(x_{j,i}=0 | r_{j,i})} = \frac{2}{\sigma_n^2} r_{j,i} \quad \forall i = 1 \ldots \mathrm{n} \;\; \text{and} \;\; j = 1,2 \qquad (5).$$

Each LDPC decoder performs local iteration with a terminating criteria based on a maximum number of iterations (50). The outputs of the LDPC decoders are hard information of the estimated transmitted sequences and soft information of the LLRs. The hard estimates are used to estimate the source correlation following eq 6.

$$LLRz = \log(k - w_H(z)) / w_H(z) \qquad (6).$$

Where k is the data block size and w_H represent the hamming weight of sequences z, where $Z = XOR(\hat{u}_{1,} \hat{u}_2)$.

At each global iteration, the estimated sequences u_1 and u_2 and the estimation of the source correlation are used to evaluate the extrinsic information as show in eq. 7.

$$\begin{aligned} LLRex(\hat{u}_{1,\mathrm{j}}) &= sign(LLRz(z)) \cdot sign(LLR(u_{2,\mathrm{j}})) \cdot min(|LLRz|(z), |LLR|(u_{2,\mathrm{j}})) \\ LLRex(\hat{u}_{2,\mathrm{j}}) &= sign(LLRz(z)) \cdot sign(LLR(u_{1,\mathrm{j}})) \cdot min(|LLRz|(z), |LLR|(u_{1,\mathrm{j}})) \end{aligned} \qquad (7).$$

Let $\hat{l}_1$ and $\hat{l}_2$ be the reconstructed index pair and $LLR(l_1)$ and $LLR(l_2)$ be the corresponding log-likelihood ratio of each bit of the index pair. If the index pair is not a valid index assignment, we locate the bit with the smallest log-likelihood ratio

$$LLR_{min}(l_{j,i}) = arg\, min(LLR(l_{1,i}), LLR(l_{2,i}))$$

and change its value according to its corresponding value coming from the reciprocal index,

$$LLR_{min}(l_{j,i}) = LLR(l_{k,i})$$

where, for the case of two descriptions if j=1, k=2 and vice versa. If a valid index pair is found the process is stopped and the reconstructed index pair is sent to the MD lattice vector decoder. Else, the next bit is flipped following the same process.

The resulting indexes are sent to the multiple description lattice quantization decoder, who estimates the original index and the original image is reconstructed.

5 SIMULATION RESULTS

In the following, we provide experimental results for the behavior of the proposed algorithms under various channel conditions. The proposed scheme was experimentally evaluated for the transmission of a 512 x 512 grayscale 'Lena' image. The channel was modeled as a flat fading channel with average SNR=10db, whereas a BPSK modulation scheme was utilized for the transmission. The LDPC codes were the same as the ones used in DVB-S2 with a total block size of 61800 bits.

In figures 14 and 12, we examined the robustness of the coding scheme in term of the reconstructed image quality with and without the joint decoding for various channel SNRs. The source is encoded at 0.2 bpp and 0.5 bpp for each description and the LDPC codes at 4/5 resulting in transmission rates 0.25 and 0.625.

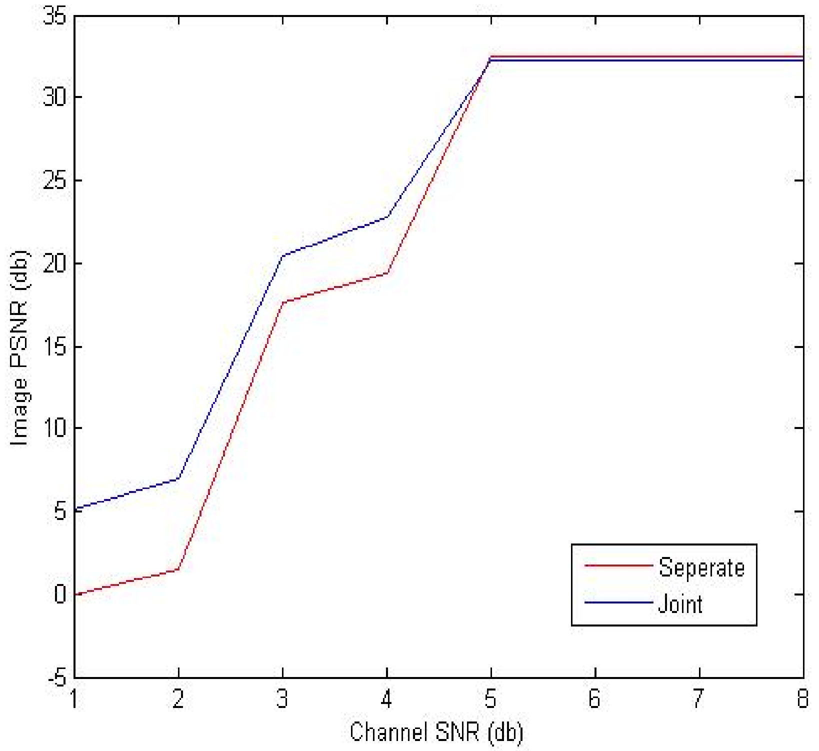

Illustration 14: PSNR vs SNR at 0.25 bpp

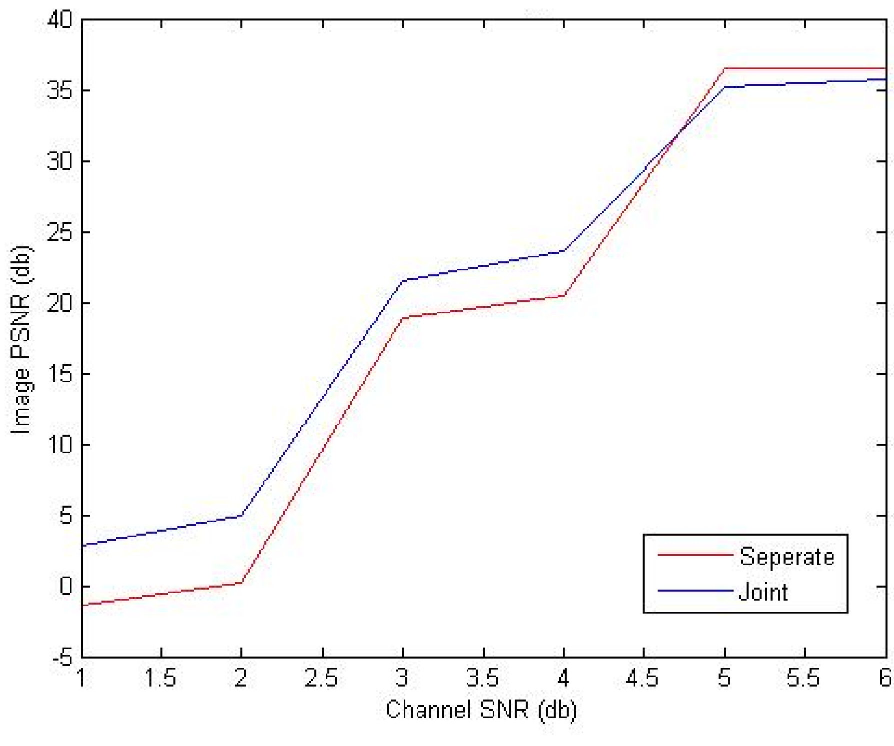

Illustration 15: PNSR vs SNR at 0.625 bpp

The next Table presents the received image PSNR for various channel BER under the binary symmetric channel model and the corresponding results from [5.1] and [5.2]

Separate decoding of LDPC codes

	Channel BER	
Rate	0,08	0,03
0,6666 (0,5+2/3)	28,96	32,96
0,994 (0,5+1/2)	36,45	36,45
0,3 (0,2+1/2)	32,43	32,43
0,2666 (0,2+2/3)	32,43	32,43
0,2 (0,1+1/2)	29,28	
0,13 (0,1+2/3)	29,28	
0,45 (0,3+1/2)	34.16	34.16
0,4 (0,3+2/3)	34.16	34.16

Joint decoding of LDPC codes

	Channel BER	
Rate	0,08	0,03
0,6666 (0,5+2/3)	36,38	
0,994 (0,5+1/2)	36,45	
0,3 (0,2+1/2)	32,43	32,43
0,2666 (0,2+2/3)	32,43	32,43
0,2 (0,1+1/2)	29,28	
0,13 (0,1+2/3)	29,28	
0,45 (0,3+1/2)	34,10	34.10
0,4 (0,3+2/3)	34,17	34.17

Comparison with [5.2]

	0,24bpp	1bpp
Ref	28,84	36,32
Separate Dec.	29,28	36.4952
Joint Dec.	29,29 (0,1+4/5)	36.6020 (0,5 + 4/5)

The following table compares the results of the proposed scheme versus the results of [6.4]. The channel considered was a flat fading channel with an average SNR 10db. In both cases of 0,24 and 1bpp, the decoded image quality of the suggested algorithm is better than the referenced. Especially in the case of small rate, we observe an increase in quality of 0.5 db. Another point of interest is that in small rate, there is no significant gain from the joint decoding of the multiple descriptions.

LENNA @ 0.5bpp	PSNR		
BER	Ref1	Ref2	Proposed
0.01	24.79	20.2	28.51
0.001	28.62	27.5	32.22

LENNA @ 1bpp	PSNR		
BER	Ref1	Ref2	Proposed
0.01	29.99	N/A	35.10
0.001	33.89	N/A	35.23

Next, we present the 'lenna' and the 'baboon' image after they have been transmitted over a binary symmetric channel with The following image are encoded with the proposed algorithm and subjected to various bit error rates.

Illustration 16: Lenna encoded at 0,5bpp with 0,01 BER

Illustration 17: Figure X. Lenna encoded at 1bpp with 0,001 BER

Illustration 18: Lenna encoded at 1bpp with 0,01 BER


Illustration 19: Lenna encoded at 0,96bpp with 0,05 BER


Illustration 20: Lenna encoded at 0,88bpp with 0,001 BER

Illustration 21: Lenna encoded at 0,5bpp with 0,001 BER

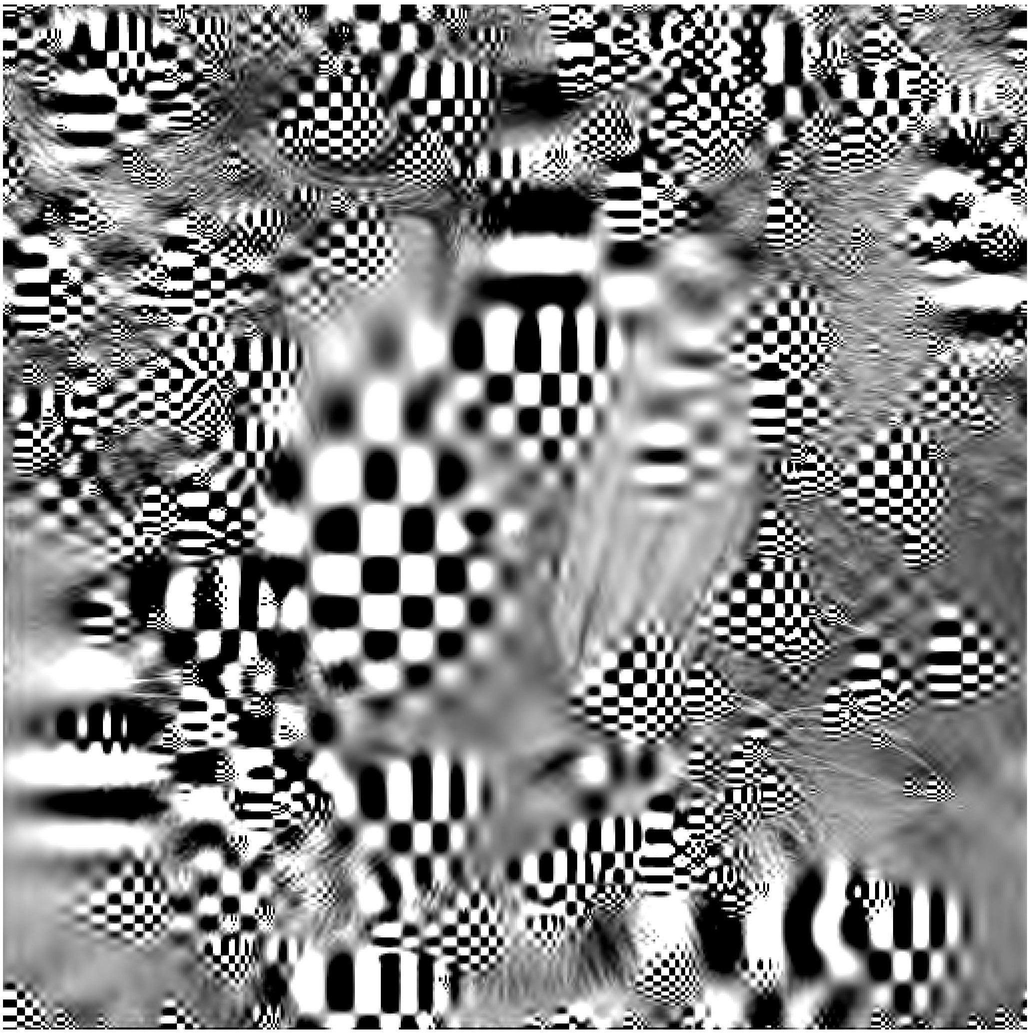

Illustration 22: Baboon Seperate decoding, BER=0.05, 0.4bpp,LDPC 5/6

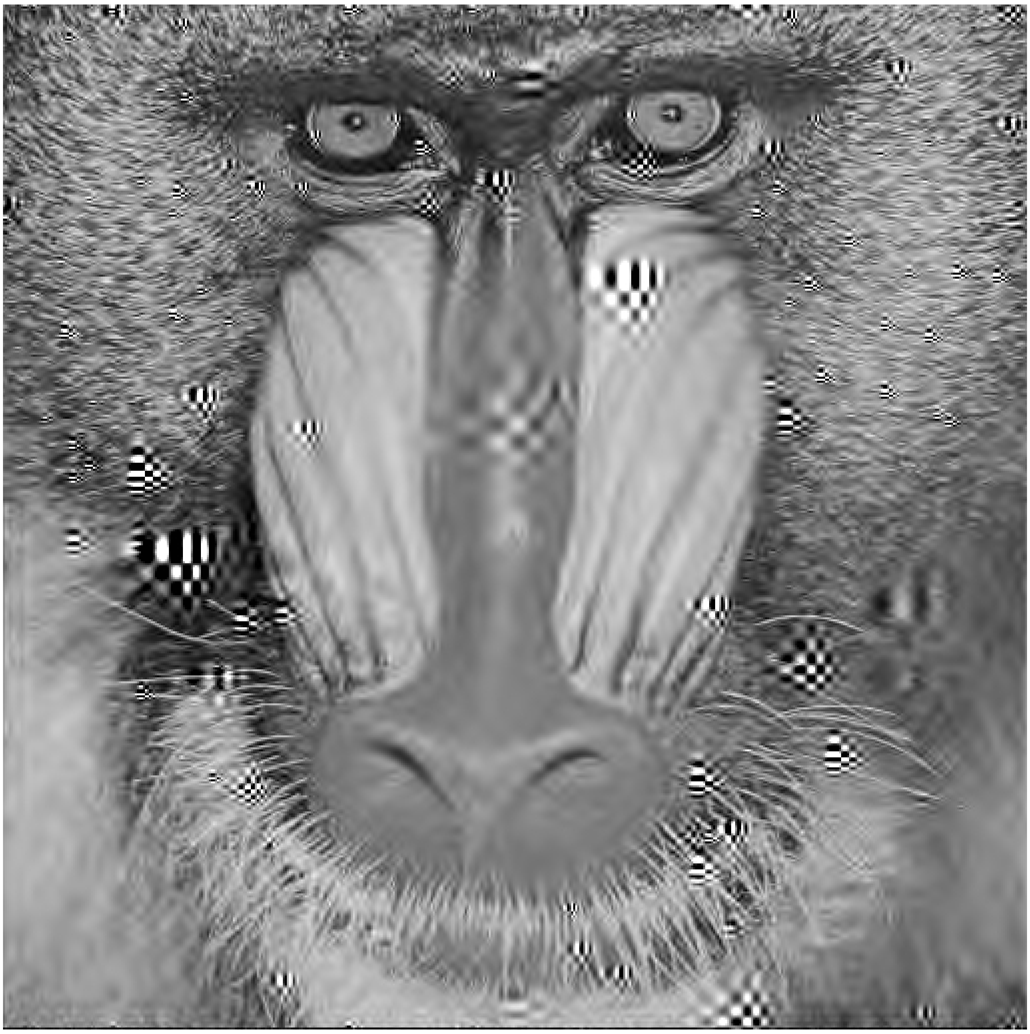

Illustration 23: Baboon Joint decoding, BER=0.05, 0.4bpp,LDPC 5/6

Illustration 24: Baboon Seperate decoding, BER=0.05, 0.2bpp,LDPC 5/6

Illustration 25: 24: Baboon Joint decoding, BER=0.05, 0.2bpp,LDPC 5/6

6 Conclusions and Further Work

In this work, we examined robust methods for image transmission over wireless channel. Image transmission and in general video transmission is a very challenging task in terms of bandwidth and delay tolerance. On the other hand, wireless channel are prone to errors and have constantly varying characteristics. In order to combat transmission error, we presented a Source-Channel Coding scheme for image transmission over wireless channels. Our scheme consist of two parts, the source coding and the channel coding. Multiple description coding has been proposed as a method for generation of multiple streams of the source information and transmitting them over independent channels. The generation of the multiple stream is archived through multiple description lattice vector quantization. Each description is independently protected with a low-density parity check code. At the receiver the decoding of the multiple stream is performed jointly, taking the correlation of the descriptions under account.

We examined the proposed scheme in two channels, namely the binary symmetric channel and the Gaussian channel and made extensive experiments under various channel conditions.

The scheme offers minimum delay, fast decoding algorithms and good results with minimum overhead.

In future work, the proposed source-channel scheme should be applied to video. Most highly qualified candidates are 3D-SPIHT, MC-SPIHT, In addition, the scheme should be evaluated in Multi-Input-Multi-Output (MIMO) channels. A closed form for the Rate-Distortion function should also be formulated. As any other model, the final test of its reliability is to implement and examine in real wireless channel conditions

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