

## Syndrome Coding of Video with LDPC Codes

Sivaparkash Reddy      Aparna.P      Dr Sumam David SMIEEE

*Department of Electronics and Communication*

*National Institute of Technology Karnataka, Surathkal, Mangalore 575025 INDIA*

E-mail: sumam@ieee.org

### Abstract

*In this paper we present the simulation results of the video coding system based on the principle of distributed source coding. Unlike conventional video coding system, this system exploits source statistics at the decoder, thus reversing the complexity model. Current implementation uses LDPC codes for syndrome coding.*

### 1 Introduction

As the trend towards media convergence continues, need to have advanced video compression techniques become more critical. Current video standards like ISO MPEG and ITU H.26x schemes have successfully addressed the issues involved in the design of good compression techniques. However they support a *Broadcast* model where in high encoder complexity is not an issue. These complex encoders efficiently code the video data by exploiting source statistics at the encoder and distributes them to simple cheap decoder. This *Broadcast* model of video coding scheme is inappropriate for newly emerging wireless video applications like mobile video cameras, wireless PC cameras, disposable video cameras, network camcorders, wireless video sensor networks etc. The *wireless-video* model demands for simple encoder as the power and computational resources are of primary concern in the wireless scenario. Computational complexity of the conventional video encoder is dominated by motion-compensated prediction operation required to strip the temporal redundancy existing between the adjacent video frames. The *wireless-video* model shifts the entire bulk of computation to the decoder, thus exploiting the source statistics at the decoder. This perception is based on the two fundamental results developed by Slepian-Wolf [1] for lossless coding and Wyner-Ziv [2] for lossy coding with decoder side information. This new approach of video coding combines the traditional video coding techniques with the information-theoretic principles that describes source coding with side information at the decoder. In the design

of a new video coding paradigm, issues like compression efficiency, robustness to packet losses, encoder complexity are of prime importance in comparison with conventional coding system. In this paper we present the simulation results of distributed video coding with syndrome coding as in PRISM [3], using LDPC codes for coset channel coding [4].

### 2 Background

#### 2.1 Slepian-Wolf Theorem for lossless Distributed coding [1]

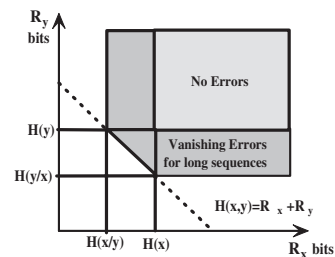


Figure 1. Admissible Rate Region [1]

Consider two correlated information sequences  $X$  and  $Y$ . Encoder of each source is constrained to operate without the knowledge of the other source while the decoder has access to both encoded binary message streams. The problem that Slepian-Wolf theorem addresses is to determine the minimum number of bits per source character required for encoding the message stream in order to ensure accurate reconstruction at the decoder. Considering separate encoder and the decoder for  $X$  and  $Y$ , the rate required is  $R_X \geq H(X)$  and  $R_Y \geq H(Y)$  where  $H(X)$  and  $H(Y)$  represents the entropy of  $X$  and  $Y$  respectively. Slepian-Wolf [1] showed that good compression can be achieved with joint decoding but separate encoding. For doing this an admissible rate region is defined as shown in Fig(1) given

by:

$$R_X + R_Y \geq H(X, Y) \quad (1)$$

$$R_X \geq H(X/Y), R_Y \geq H(Y) \quad (2)$$

$$R_X \geq H(X), R_Y \geq H(Y/X) \quad (3)$$

Thus Slepian-Wolf [1] showed that Eq(1) is the necessary condition and Eq(2) or Eq(3) are the sufficient conditions required to encode the data in case of joint decoding. With the above result as the base, we can consider the distributed coding with side information at the decoder. Let  $X$  be the source data that is statistically dependent to the side information  $Y$ . Side information  $Y$  is separately encoded at a rate  $R_Y \geq H(Y)$  and is available only at the decoder. Thus as seen from Fig(1)  $X$  can be encoded at a rate  $R_X \geq H(X/Y)$ .

## 2.2 Wyner-Ziv rate distortion theory[2]

Aaron Wyner and Jacob Ziv [2] extended Slepian-Wolf theorem and showed that conditional Rate-MSE distortion function for  $X$  is same whether the side information is available only at the decoder or both at encoder and decoder; where  $X$  and  $Y$  are statistically dependent Gaussian random processes. Let  $X$  and  $Y$  be the samples of two random sequences representing the source data and side information respectively. Encoder encodes  $X$  without access to side information  $Y$ . Decoder reconstructs  $\hat{X}$  using  $Y$  as side information. Let  $D = E[d(\hat{X}, X)]$  is the acceptable distortion. Let  $R_{X/Y}(D)$  be the rate required for the case where side information is available at the encoder also and  $R_{X/Y}^{WZ}(D)$  represent the Wyner-Ziv rate required when encoder doesn't have access to side information. Wyner-Ziv proved that Wyner-Ziv rate distortion function  $R_{X/Y}^{WZ}(D)$  is the achievable lower bound for the bitrate for a distortion  $D$

$$R_{X/Y}^{WZ}(D) - R_{X/Y}(D) \geq 0 \quad (4)$$

They also showed that for Gaussian memoryless sources

$$R_{X/Y}^{WZ}(D) - R_{X/Y}(D) = 0 \quad (5)$$

As a result source sequence  $X$  can be considered as the sum of arbitrarily distributed side information  $Y$  and independent Gaussian Noise.

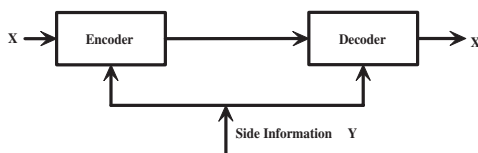


Figure 2. Conventional Coding System

Distributed video coding is based on these two fundamental theories, specifically works on the Wyner-Ziv coding considering a distortion measure. In such a coding system the encoder encodes each video frame separately with respect to the correlation statistics between itself and the side information. The decoder decodes the frames jointly using the side information available only at the decoder. This video paradigm is as opposed to the conventional coding system where the side information is available both at the encoder and decoder as shown in Fig(2)

## 2.3 Syndrome Coding [5]

Let  $X$  be a source that is to be transmitted using least average number of bits. Statistically dependent side information  $Y$ , such that  $X = Y + N$  is available only at the decoder. The encoder must therefore encode  $X$  in the absence of  $Y$ , whereas the decoder jointly decodes  $X$  using  $Y$ . Distributed source encoder compresses  $X$  into syndromes  $S$  with respect to a Channel code  $C$  [6]. Decoder on receiving the syndrome can identify the coset to which  $X$  belongs and using side information  $Y$  can reconstruct back  $X$ .

## 3 Implementation

### 3.1 Encoder

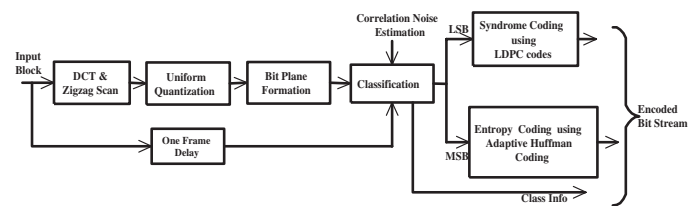


Figure 3. Video Encoder

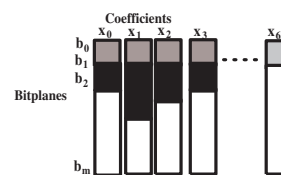


Figure 4. Bit Planes for each coefficient Blocks

The encoder block diagram is shown in the Fig(3). The video frames are divided into blocks of  $8 \times 8$  and each block is processed one by one. Block DCT (Discrete Cosine

Transform) is applied to each 8x8 block (or 16x16) and the DCT coefficients are zig-zag scanned so that they are arranged as an array of coefficients in order of their importance. Then the transformed coefficients are uniform quantized with reference to target distortion measure and desired reconstruction quality. After quantization, a bitplane is formed for each block as shown in Fig(4) [3]. Main idea behind Distributed video coding is to code source  $X$  assuming that the side information  $Y$  is available at the decoder such that  $X = Y + N$ , where  $N$  is Gaussain random noise. This is done in the classification step where bitplane for each coefficient is divided into different levels of importance. Classification step strongly rely on the correlation Noise structure  $N$  between the source block  $X$  and the side information block  $Y$ . Less is the correlation noise between  $X$  And  $Y$ , more is the similarity and hence less number of bits of  $X$  can be transmitted to the decoder. In order to classify the bitplanes an offline training is done for different types of video files without any motion search. On the basis of offline process 16 types of classes are formed, where each class considers different number of bitplanes for entropy coding and syndrome coding for each coefficients in the block. In the classification process, MSE (mean square error) for each block is computed with respect to the zero motion block in the previous frame. Based on the MSE and the offline process appropriate class for that particular block is choosen. As a result some of the least significant bit planes are syndrome coded and some of the bitpalnes that can be reconstructed from side information are totally ignored. The syndrome coding bitplanes are shown in black and gray in Fig(4) and skip planes are shown in white in Fig(4). Skip planes can be reconstructed back using side information at the decoder and hence need not be sent to the decoder. The important bits of each coefficient that cannot be determined by side information has to be syndrome coded [3]. In our implementation we code two bitplanes using coset channel coding and the remaining syndrome bitplanes using Adaptive Huffman coding. Among the syndrome coding bitplanes we code the most significant bit planes using Adaptive Huffman coding. The number of bitplanes to be syndrome coded are directly used from class information that is hard coded. Hence we need not send four-tuple data (run,depth,path,last) as in PRISM [3]. Rest of the least significant bitplanes are coded using coset channel coding. This is done by using a parity check matrix  $H$  of a  $(n, k)$  linear channel code. Compression is achieved by generating syndrome bits of length  $(n - k)$  for each n bits of data. These syndrome bits are obtained by multiplying the source bits with the parity check matrix  $H$  such that

$$S = Hb_X.$$

where  $S$  represents the syndrome bits.  
 $H$  represents the parity check matrix of linear channel code.

$b_X$  represents the source bits.  
 These syndromes identifies the coset to which the source data belongs to. In this implementation we have considered two biplanes for coset coding marked gray in the Fig(4). We have implemented this using *irregular 3/4* rate LDPC coder [4].

### 3.2 Decoder

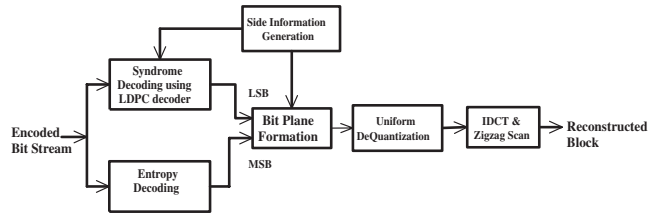
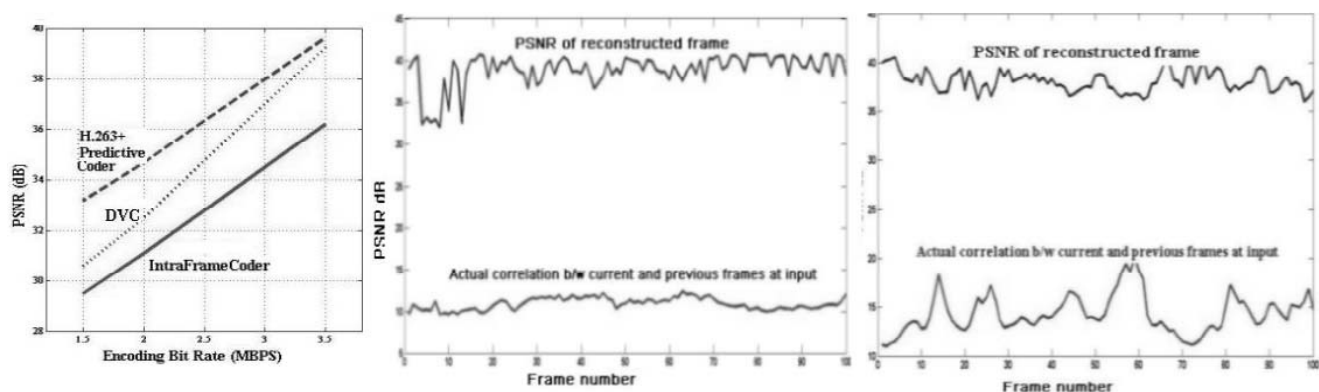


Figure 5. Video Decoder

The Decoder block diagram is shown in the Fig(5). The entropy coded bits are decoded by an entropy decoder and the coset coded bits are passed to the LDPC decoder. In this implementation, previous frame is considered as the side information required for syndrome decoding. Once the syndrome coded bits are recovered they identify the coset to which  $X_i$  belongs and hence using the side information  $Y_i$  we can correctly decode the entire bits of  $X_i$ . The quantized codeword sequence are then dequantized and inverse transformed to get the original coefficients.

### 4 Simulation Results

The encoder and decoder block as shown in Fig(3) and Fig(5) respectively are implemented and some preliminary simulation results are presented in this paper for the *Football* in *QCIF* resolution with a frame rate of 30 fps. The rate distortion performance and the error resilience characteristics of the Distributed video coder is presented in this paper. As seen from the Fig(6a) distributed video coder performs 2-5dB better than DCT based intraframe coder and performs closer to H.263+ predictive coder [7] in terms of rate-distortion performance for *Football* file. With some enhancements to the current coding scheme such as accurate modeling of correlation statistics between the source data and the side information, proper motion search module for side information generation etc, better rate-distortion performance can be achieved with a low complexity encoder model. Error Resilience characteristics of Distributed video scheme is as shown in Fig(6b) for *Football* and Fig(6c) for *Foreman*. Effect on the quality of the reconstructed video sequence is seen by dropping 4th, 10th, 20th frames at the decoder in our implementation. It is seen that distributed



**Figure 6. (a) Rate-Distortion Performance for *football* (b) Error resilience characteristics of DVC, 4th, 10th, 20th frames are lost for *football*. (c) Error resilience characteristics of DVC, 4th, 10th, 20th frames are lost for *foreman***

video coder recovers quickly and maintains the SNR in 37-39dB. In Distributed video scheme, decoding is dependent on the side information  $Y$  that is universal for all source data  $X$  as long as correlation structure is satisfied.

## 5 Conclusion

In this paper we have tried PRISM [3] like implementation using LDPC coset channel coding. By proper modelling of correlation structure of source and the side information for video we can achieve better compression performance with better quality of reconstructed video sequence. However the main aim of distributed video coding scheme is to reduce encoder complexity to conform with *wireless-video* model, which seems to be satisfied. Distributed codec is more robust to packet/frame loss due to the absence of prediction loop in the encoder. In a Predictive coder accuracy of decoding is strongly dependent on a single predictor from the encoder, loss of which results in erroneous decoding and error propagation. Hence Predictive coder can recover from packet or frame loss by only some extent. The quality of the reconstructed signal for the same CR can be improved by performing more complex motion search. However it is seen that the current implementation operates well in high quality (PSNR of order of 30dB) regime. The extension to lower bit rates without any compromise in the quality so that it is comparable with the conventional codecs will be the next part of the work.

## References

[1] J.D.Slepian and J.K.Wolf, Noiseless coding of correlated information sources, *IEEE Transactions on Information Theory*, vol.IT-19, pp.471-480, July 1973.

[2] A.D.Wyner and J.Ziv, The rate-distortion function for source coding with side information at the decoder, *IEEE Transactions on Information Theory*, vol.IT-22, no.1, pp.1-10, Jan 1976.

[3] Rohit Puri, Abhik Majumdar and Kannan Ramchandran, PRISM: A video Coding Paradigm with Motion Estimation at the Decoder, *IEEE Transactions On Image Processing*, Vol 16, No 10, October 2007.

[4] Angelos D.Liveris, Compression of Binary Sources with side information at the Decoder using LDPC codes, *IEEE Communication Letters*, Vol 6, No 10, October 2002.

[5] S.S.Pradhan and K.Ramchandran, Distributed source coding using syndromes(DISCUS): Design and construction, *Proc.IEEE Data Compression Conference*, Snowbird, UT, pp.158 -167, Mar.1999.

[6] R.Puri and K.Ramchandran, PRISM: A new robust video coding architecture based on distributed compression principles, *Proc. Allerton Conference on Communication, Control and Computing*, Allerton, IL, Oct 2002.

[7] G.Cote, B.Erol, M.Gallant, and F.Kossentini, H.263+: Video coding at low bitrates, *IEEE Transactions.Circuits Sys. Video Technology*, Vol 8, No 7, pp 849-866, November 1998.