Distributed Video Coding:
A Summary and Roadmap

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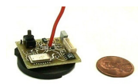
Distributed Source Coding (DSC)

- Compression of two or more physically separated sources
  - The sources do not communicate with each other (hence distributed coding)
  - Decoding is done jointly (say at the base station)
- Related to the CEO problem
  - A CEO employs L agents who independently obtain corrupted versions of a source
  - The agents are not allowed to convene
  - What is the minimum total data rate the agents need to convey info about their observations to the CEO?
- Part of network information theory
- Recent research activities spurred by applications

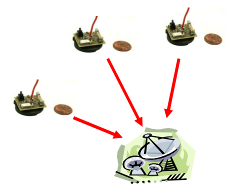
Sensor Networks

- A networks of many tiny, low-powered and cheap wireless sensors
  - Examples: Berkeley Smart Dust



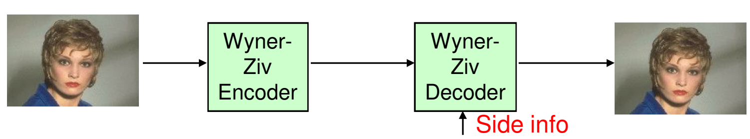
- #1 emerging technology: *MIT Technology Review*
- The next big thing: *Time Magazine*

- Applications
  - Information gathering (surveillance)
  - Environment (climate or habitat) monitoring
  - National defense (homeland security)
- The scenario for DSC
  - Sensor outputs are correlated
  - Sensors do not communicate with each other
  - Receiverless to save cost and power



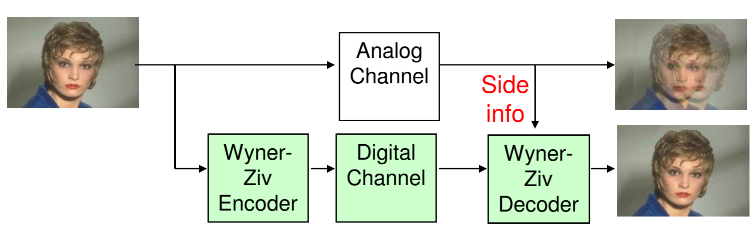
Distributed Video Coding I

- Wyner-Ziv video coding



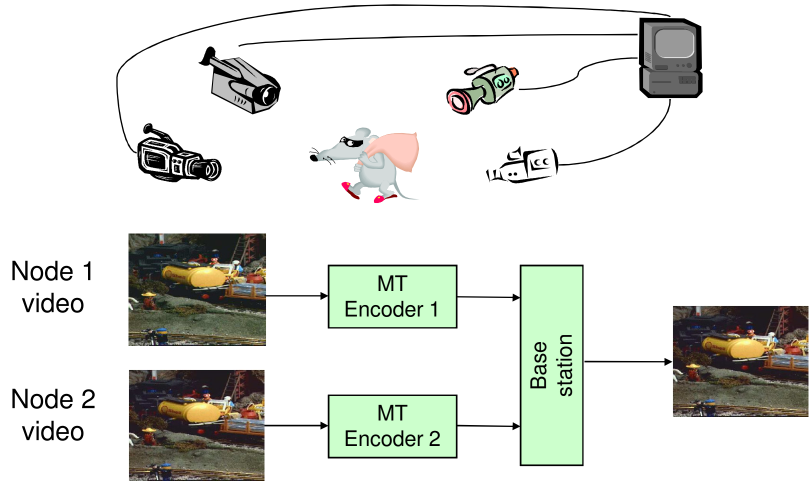
Courtesey of Bernd Girod

- Systematic source-channel coding



Distributed Video Coding II

- Multiterminal (MT) video coding



Tutorial Outline

I. Background
- Slepian-Wolf coding
- Wyner-Ziv coding
- Distributed source-channel coding
- Multiterminal source coding

II. DVC overview (start from conventional video coding)
- Work done by other groups
- Layered Wyner-Ziv video coding
- Distributed source-channel coding of video
- Multiterminal video coding

III. DVC roadmap
- Scalable Slepian-Wolf coding
- Correlation modeling and universal Slepian-Wolf coding
- Practical low-complexity and high-efficiency DVC

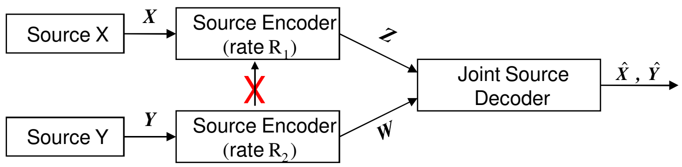
Start with Classic Source Coding

- Entropy coding techniques (zero loss)
  - Huffman/arithmetic coding, LZC, PPM, CTW, etc.
- Channel coding for near-lossless source coding
  - Exploit duality between SC and CC
- Linear CC with mxn parity-check matrix H
  - For a discrete additive channel $y = x \oplus u$
  - ML decoder selects codeword y-g_H(Hy): most likely realization among those with the same syndrome Hy
- SC with the same parity-check matrix H
  - Maps n-string source s to m-string syndrome Hs
  - ML decoder selects g_H(Hs): most likely u with Hu=Hs
- These two related problems suggest parity-check matrix H of CC as SC matrix

LDPC Code Based Source Coding

- (n,k) binary LDPC code
  - 2^k codewords of length n; 2^{n-k} syndromes/cosets
  - Encoding: n-bit input mapped to (n-k)-bit syndrome
  - Decode each syndrome/coset to its coset leader
- Brief history of CC for SC
  - Weiss'62: fixed-length SC
  - Allard et al'72 and Fung et al'73: variable-to-fixed length SC
  - Ancheta'76: BCH code based SC
  - Garcia-Frias & Zhao'02: turbo code based SC
  - Caire, Shamai & Verdu'03
    - LDPC code based SC; bit doping to guarantee lossless compression
    - Burrows-Wheeler transform to decorrelate data
- Syndrome-based SC easily extendable to near-lossless source coding with side information (SCSI)

SCSI: A Case of Slepian-Wolf Coding



- Joint encoding (Y is available when coding X)
  - Code Y at $R_2 \geq H(Y)$; use Y to predict X and then code the difference at $R_1 \geq H(X|Y)$
  - All together, $R_1 + R_2 \geq H(X|Y) + H(Y) = H(X,Y)$
- Distributed coding
  - Y is not available when coding X
  - What is the minimum rate to code X in this case?
  - **Slepian-Wolf Theorem: still H(X|Y)**
- **Separate encoding as efficient as joint encoding!**

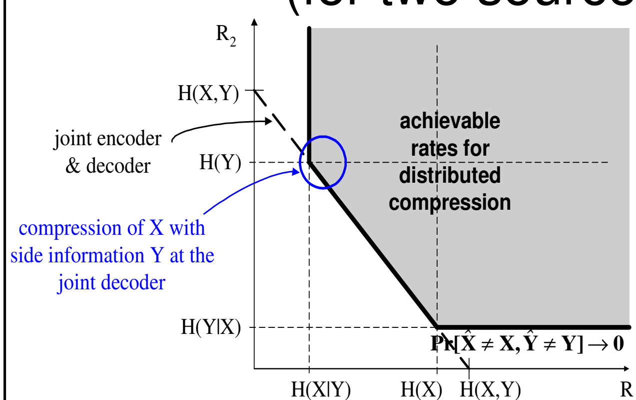
An Example

- Transmitting correlated temperature measurements from neighboring cities to the national weather center

An Example

- Assume the temperatures between College Station and Houston cannot differ by more than 3 degrees
- Joint encoding: Convey the temperatures independently to the weather center using, say 8, bits each
- Slepian-Wolf encoding: Convey the temperature in Houston using 8 bits, send the temperature in College Station in modulo 7 (using 3 bits)

The Slepian-Wolf Rate Region (for two sources)

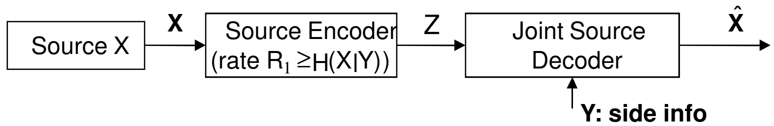


$$R_1 \geq H(X \mid Y);$$
$$R_2 \geq H(Y \mid X);$$
$$R_1 + R_2 \geq H(X, Y)$$

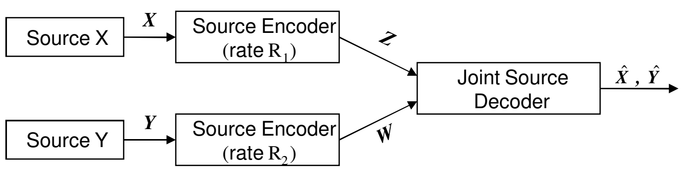
- Results can be extended to ergodic source, infinite alphabets and arbitrary # of correlated sources

The Slepian-Wolf Problem

- Start with SCSI (or asymmetric Slepian-Wolf coding) to approach the two corner points



- Then symmetric Slepian-Wolf coding to approach any point between the corner points

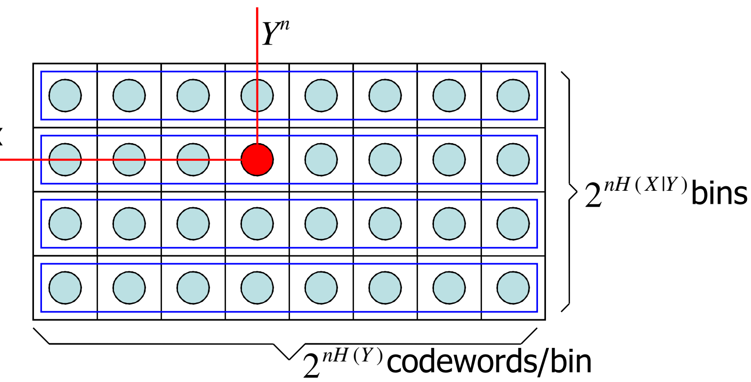


From Theory to Practice

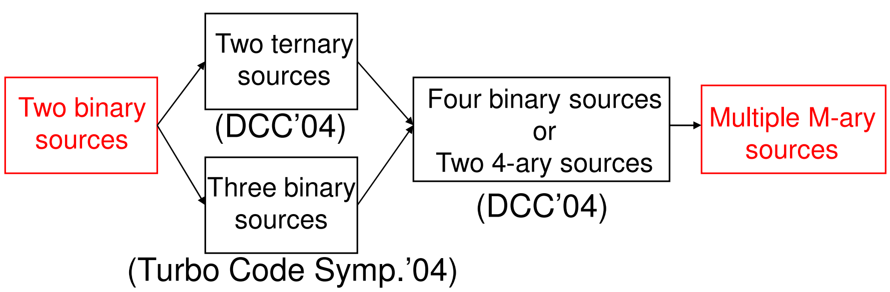
- Took almost 30 years
- The use of parity-check codes for Slepian-Wolf coding 1st suggested in Wyner's 1974 paper
  - Use of channel coding for this source coding problem
- Slepian-Wolf problem is a channel coding problem
- First practical algorithm based on coset codes
  - Pradhan & Ramchandran'99
- Capacity-approaching channel codes (turbo, LDPC codes) found only recently
- Random binning used to prove the Slepian-Wolf Theorem
  - Algebraic binning in practice

Algebraic Binning

- Need totally ~ $2^{nH(X,Y)}$ codewords to specify (X^n, Y^n)
  - Put them into $2^{nH(X|Y)}$ bins, each with $2^{nH(Y)}$ codewords
  - Use $nH(X|Y)$ bits to specify a particular bin
  - The bin index and Y^n at the decoder jointly decode (X^n, Y^n)



Asymmetric Slepian-Wolf Coding for Multiple M-ary Sources



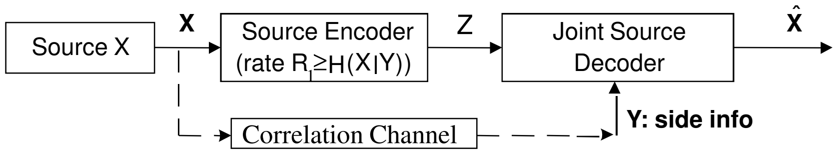
Past Work on Slepian-Wolf Coding

- For two binary sources
  - Turbo code based design (Garcia-Frias & Zhao'01, Bajcsy & Mitran'01, Aaron & Girod'02, Liveris, Xiong & Georghiades'03)
  - LDPC code based design (none before our work, ours followed by Garcia-Frias & Zhao'03 and Schonberg, Ramchandran & Pradhan'02 & '03)
- For two non-binary sources
  - Turbo code based design (Zhao & Garcia-Frias'02)

Our Work on Slepian-Wolf Coding

- We are the 1st to apply LDPC codes for Slepian-Wolf coding
  - Results very close to the Slepian-Wolf limit
- We also studied conventional turbo codes for Slepian-Wolf coding
  - Only approach that follows Wyner's scheme
  - Better than results reported by others
- Slepian-Wolf coding of multiple M-ary sources using LDPC codes
  - Two or three binary sources (2002 and 2003)
  - Two ternary sources (2003)
  - Four binary (or two 4-ary) sources (2003)
  - Two 2^m-ary sources (2003)

Slepian-Wolf Coding (SCSI)



- Y available without loss at the decoder (perfect side information)
  - Theoretical compression limit: $R_1 \geq H(X|Y)$
  - Equivalent communication channel model of the correlation
  - Proposed solution: Syndrome approach
  - Use of LDPC and Turbo codes

An Example of Slepian-Wolf Coding

- Assumptions:
  - $X,Y \in \{0,1\}^3 \rightarrow$ binary triplets
  - $H(X)= H(Y)= 3$ bits $\rightarrow$ equiprobable triplets
  - Correlation between X and Y:
    - X and Y differ ***at most in one position***

      $\Rightarrow$ Hamming distance $d_H(X,Y) \leq 1$

      $\Rightarrow$ given Y, *4 equiprobable* choices for X

      $\Rightarrow$ **$H(X|Y)=2$ bits**

- Question: If **Y perfectly known at the decoder** but not at the encoder, is it possible
  - to send **2 bits instead of 3 for X and**
  - **reconstruct X without loss?**

Slepian-Wolf Coding Example (cont.)

- Solution:
  - Form **4 sets** and send **2-bit index** of the set X belongs to:
    - set Z_{00}: {000,111}
    - set Z_{01}: {001,110}
    - set Z_{10}: {010,101}
    - set Z_{11}: {011,100}
  - In each set: 2 members at $\mathbf{d_H=3}$
  - Joint decoder: in the set indexed by Z:
    - using Y, pick $\hat{x}$ s.t. $d_H(\hat{x},Y) \leq 1$

$\Rightarrow$ **No** loss: **limit achieved losslessly!**

Syndrome Concept

- Equivalent way of viewing last example
  - Form parity-check matrix of rate 1/3 repetition code

$$H = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

  - **Syndrome=set index**
    - set (code) 0:{000,111} $\rightarrow$ syndrome= Z= 00
    - set (code) 1:{001,110} $\rightarrow$ syndrome= Z= 01
    - set (code) 2:{010,101} $\rightarrow$ syndrome= Z= 10
    - set (code) 3:{011,100} $\rightarrow$ syndrome= Z= 11
  - All 4 codes **preserve the distance properties** of the repetition code
  - Compression 3:2

More Slepian-Wolf Coding Examples

- Generalization of the previous example
  - X,Y are equiprobable (2^i -1)- bit binary sources ($i \geq 3$)
  - H(X)= H(Y)= n= 2^i -1 bits
  - Again X and Y differ ***at most in one position***
  - H(X|Y)=i bits and H(X,Y)=n+i bits
- For Slepian-Wolf coding, use the i x n parity-check matrix H of the (n,n-i) binary Hamming code. When i=3,

$$H = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \end{bmatrix}$$

- 2^i syndromes, each indexing one bin of 2^{n-i} elements of n-bit binary words
  - ***n*** bits input; ***i*** bits syndrome output
  - Compression: ***n*:*i*** **(e.g., 3:2 for *i*=2; 7:3 for *i*=3)**

General Syndrome Concept

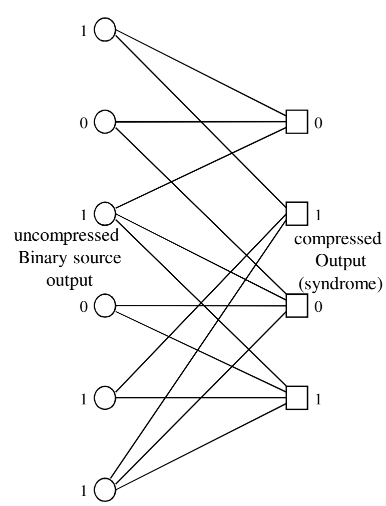
- For a linear (n,k) binary code:
  - 2^k codewords of length n
  - 2^{n-k} syndromes
    - Indexing 2^{n-k} *disjoint sets (codes)* of 2^k length-n binary words $\rightarrow$ partition of the space of all binary words of length n
    - Preserving code distance properties in each set
- Compression n:(n-k)
  - Assuming correlation modeled by a symmetric channel
    - Binary symmetric channel correlation for binary sources
    - Symmetric channel correlation for M-ary cases

General Syndrome Concept

- Extendable to **all linear codes**
  - *Especially LDPC codes!*
  - Convolutional/Turbo codes
- Key lies in correlation modeling
- A word on syndrome vs. parity bits
  - One might be tempted to use the (n-k) parity bits of (n,k) systematic codes for Slepian-Wolf coding
  - ***Syndrome-based approach is optimal and works better***
    - Because code distance property preserved
    - Good channel code -> good Slepian-Wolf code of the same performance
    - Near-capacity channel coding -> near-limit Slepian-Wolf coding performance
  - ***More on parity-based approach later***

Binary LDPC Codes

- ***Extension*** of syndrome approach
  - Correlation: BSC $\Pr[X_i \neq Y_i] = p$
  - Encoding: Binary addition at the check nodes
  - Decoding:
    - Initialize left nodes with side information
    - Change of sign at right nodes with nonzero value



LDPC Decoder

- Sum-product decoding algorithm for BSC
  - "Received values" Y (variable node input): **side information**
  - Code selection by syndrome:
    - ***Only change* at the check nodes**
      - For the j^{th} check node (degree c_j), let s_j be the corresponding syndrome bit $\rightarrow$ **"tanh-rule"** becomes:

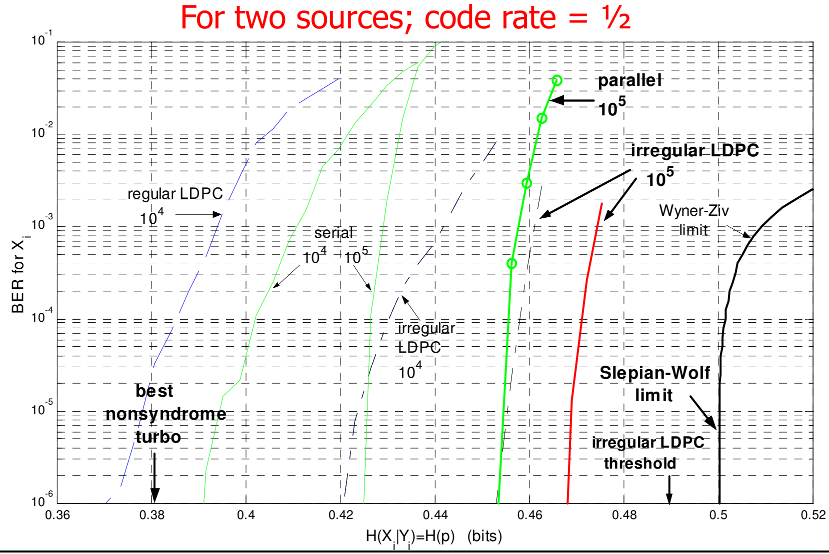
$$\tanh\left(\frac{u_{kj}^{out}}{2}\right) = (1-2s_j)\prod_{i=1,i\neq k}^{c_j}\tanh\left(\frac{u_{ij}^{in}}{2}\right)$$

$\Rightarrow$ Just **change of sign** for *nonzero syndrome components*

- Very good results expected

Slepian-Wolf Coding Results

For two sources; code rate = ½

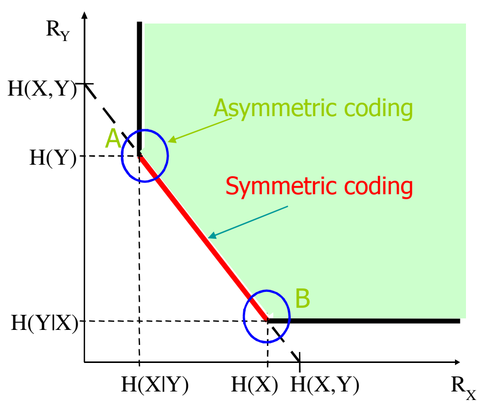


Slepian-Wolf Coding of two 2^m-ary Sources

- Follow multi-level LDPC code design procedure
- One binary LDPC code for each bit
- Multi-stage decoding
- Important Slepian-Wolf coding problem in its own right
- Integral part of our proposed framework for Wyner-Ziv coding
  - Achieves lossless compression of quantized X with side information Y
  - Can be viewed as a conditional entropy coder

Symmetric Slepian-Wolf Coding

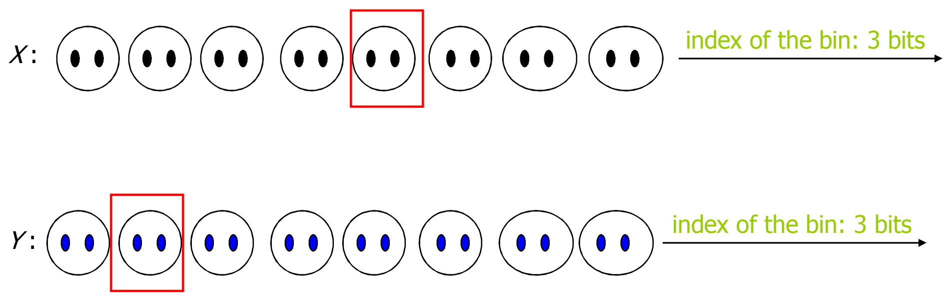
- Approaching any point on the sum-rate bound



$$R_X \geq H(X \mid Y);$$
$$R_Y \geq H(Y \mid X);$$
$$R_X + R_Y \geq H(X,Y)$$

Random Binning: Symmetric case

- Code X and Y at $R_x = R_y = 3$ bits; Total transmission rate $R_x + R_y = 3+3=6$ bits

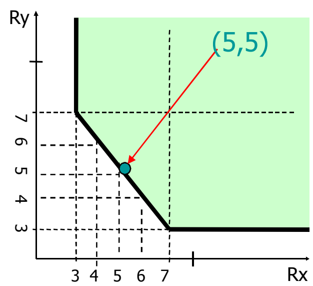


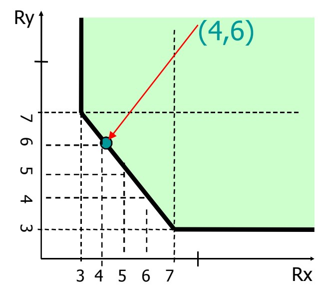
Symmetric Slepian-Wolf coding

- Asymmetric coding: Each bin is a coset of channel code (CC) indexed by its syndrome
- How to construct binning scheme for non-asymmetric coding?
- Extension to the symmetric case (Pradhan & Ramchandran)
- Generate CC C and partition it into non-overlapping subcodes C_1 and C_2
- Assign subcode C_i to encoder i
- We provide a precise and comprehensive interpretation of generalized coset codes
- Perform efficient code designs

Symmetric Slepian-Wolf Coding Example

- Two uniformly distributed sources (*X* and *Y*)
- Slepian-Wolf bound: $R_X+R_Y=H(X,Y)=10$ bits
- Asymmetric coding: $R_X=H(X)=7,\ R_Y=H(Y|X)=3$
- Symmetric coding: $R_X=R_Y=5$ or $R_X=4;\ R_Y=6$ bits!





Symmetric Slepian-Wolf Coding Example

- Start with a systematic *(7,4) Hamming* code *C*
- Partition it into G1 & G2 (for $R_X=R_Y=5$)

$$G_{4x7}=[I_4 \,\vdots\, P]=\begin{bmatrix} 1&0&0&0&1&0&1\\ 0&1&0&0&1&1&0\\ 0&0&1&0&1&1&1\\ 0&0&0&1&0&1&1 \end{bmatrix}\quad \begin{matrix} G1=[I_2\ \ O_{2x2}\ \ P1_{2x3}] \\ G2=[O_{2x2}\ \ I_2\ \ P2_{2x3}] \end{matrix}$$

- Form H1 and H2 (5 rows each) from G1 & G2

$$H1_{5x7}=\begin{bmatrix} O_{2x2} & \multirow{2}{*}{I_5} \\ P1^T_{3x2} & \end{bmatrix}\qquad H2_{5x7}=\begin{bmatrix} I_2 & O_{2x2} & O_{2x3} \\ O_{3x2} & P2^T_{3x2} & I_3 \end{bmatrix}$$

Symmetric Slepian-Wolf Coding Example

- Suppose $x = [\,a_1\ \ v_1\ \ q_1\,] = [\,00\ \ 10\ \ 110\,]$

  $y = [\,u_2\ \ a_2\ \ q_2\,] = [\,01\ \ 10\ \ 110\,]$

- Syndrome encoding

$$s_1^T = H1\,x^T = \begin{bmatrix} v_1^T \\ P1^T a_1^T \oplus q_1^T \end{bmatrix} = [\underbrace{1\ 0}_{\text{inserted}}\ \ \underbrace{1\ 1\ 0}_{\text{coded}}]^T \longleftarrow \text{5 bits!}$$

$$s_2^T = H2\,y^T = \begin{bmatrix} u_2^T \\ P2^T a_2^T \oplus q_2^T \end{bmatrix} = [\underbrace{0\ 1}_{\text{inserted}}\ \ \underbrace{0\ 0\ 1}_{\text{coded}}]^T \longleftarrow \text{5 bits!}$$

Symmetric Slepian-Wolf Coding Example

- Decoding: From length-7 vectors from syndromes

$$t_1^T = \begin{bmatrix} O_{2x1} \\ v_1^T \\ P_1^T a_1^T \oplus q_1^T \end{bmatrix} = [\underbrace{0\ 0}_{\text{added}} \overbrace{1\ 0 \,\vdots\, 1\ 1\ 0}^{S_x \text{ transmitted}}]^T \qquad x^T = \begin{bmatrix} a_1^T \\ v_1^T \\ q_1^T \end{bmatrix}$$

$$t_2^T = \begin{bmatrix} u_2^T \\ O_{2x1} \\ P_2^T a_2^T \oplus q_2^T \end{bmatrix} = [\underbrace{0\ 1}_{S_Y \text{ transmitted}} \overbrace{0\ 0}^{\text{added}} \underbrace{0\ 0\ 1}_{S_Y \text{ transmitted}}]^T \qquad y^T = \begin{bmatrix} u_2^T \\ a_2^T \\ q_2^T \end{bmatrix}$$

- Find codeword c in C closest to $t = t_1 \oplus t_2 = [01 \,\vdots\, 10 \,\vdots\, 111]$
- Since no errors: $c = x \oplus y \oplus t_1 \oplus t_2 = [\underbrace{0010}_{[\,a_1\ a_2}\,\vdots\,\underbrace{111}_{[a_1\ a_2]P\,]}]$

$\hat{x} = a1G1 \oplus t1 = [0010110] = x;\quad \hat{y} = a2G2 \oplus t2 = [0110110] = y$

Symmetric Slepian-Wolf Coding Example

- For $R_X=4;\ R_Y=6$ *bits*, partition G *differently*

$$G_{4x7}=[I_4 \vdots P]=\left[\begin{array}{ccc:c:ccc} 1&0&0&0&1&0&1\\ 0&1&0&0&1&1&0\\ 0&0&1&0&1&1&1\\ \hdashline 0&0&0&1&0&1&1 \end{array}\right] \quad \begin{array}{l} G1=[I_3\ \ O_{3x1}\ \ P1_{3x3}] \\ G2=[O_{1x3}\ \ I_1\ \ P2_{1x3}] \end{array}$$

- Form H1 and H2 (4 and 6 rows) from G1 & G2

$$H1_{4x7}=\left[\begin{array}{c:c} O_{1x3} & \\ P1^T_{3x3} & I_4 \end{array}\right] \qquad H2_{6x7}=\left[\begin{array}{c:c:c} I_3 & O_{3x1} & O_{3x3} \\ O_{3x3} & P2^T_{3x1} & I_3 \end{array}\right]$$

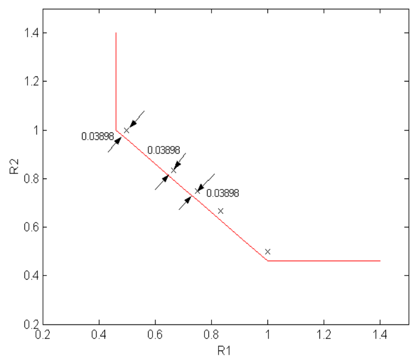
- Encoding/decoding proceeds similarly as in $R_X=R_Y=5$

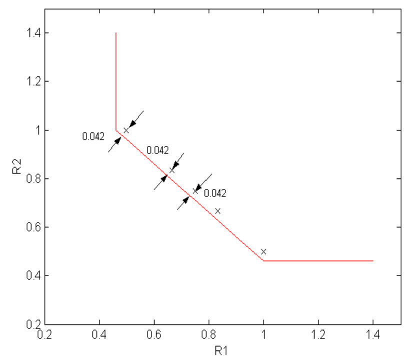
Extension to Multiple Sources

- Proposition: For coding L sources $X_1,\ldots,X_L$ with code $C\ (n,k,t)$, if correlation is such that $\omega_H(x_1\oplus\cdots\oplus x_L)\leq t$, then decoding error equals zero. If $k=n(1-H(X_1|X_2\ldots X_L))$, then $C(n,k,t)$ reaches the theoretical limit.
- Applicable to coding for lossless multiterminal networks
- Can be combined with network coding by using a single code for the entire network!

Results (Two Sources)

Two uniformly distributed sources. Correlation: BSC



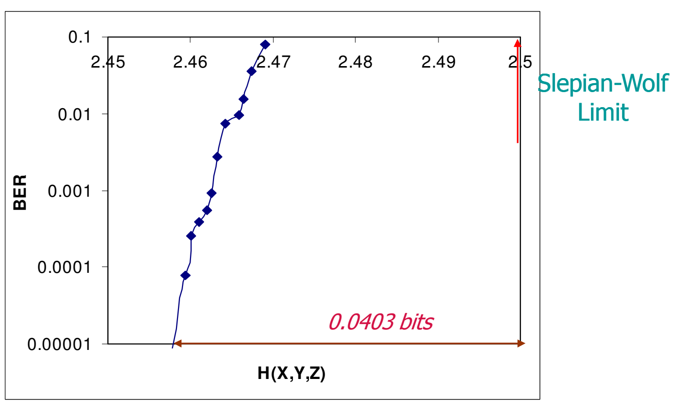


IRA code: inf. block length $k=10^5$ *Turbo code : inf. block length $k=10^5$*

<u>Uniform performance loss of 0.04 bit!</u>

Results (Three Sources)

Three uniformly distributed sources. Correlation: $\omega_H(x \oplus y \oplus z) \le p$



IRA code: inf. block length $k=10^5$, $R_X=R_Y=R_Z$

<u>The SAME loss of 0.04 bit as with two sources!</u>

Summary on Slepian-Wolf Coding

- Cast it as a channel coding problem
- Significant progresses made so far (by leveraging research results on channel coding)
- The syndrome-based approach
  - A single code approaches sum-rate limit!
  - Enables efficient code design
  - No encoder/decoder complexity increase over the asymmetric case
  - Inherent error detection capability
  - Simple implementation for all linear block CC
- Many open problems (more in Part III)

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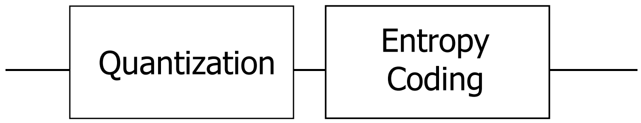
Classic Lossy Source Coding

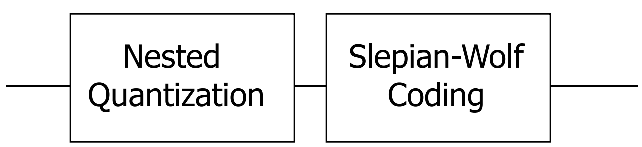
- For i.i.d Gaussian sources



- ECSQ performs 1.53 dB away from the R-D function
- Entropy-constrained hexagonal lattice quantization performs 1.36 dB away from the R-D function
- ECTCQ performs 0.2 dB away from the R-D function

Lossy SCSI (Wyner-Ziv Coding)

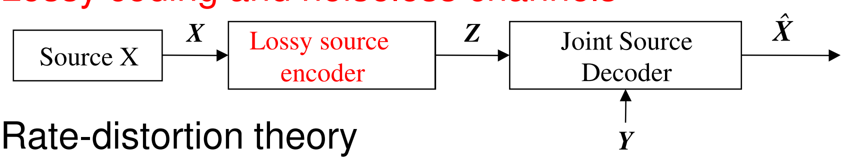
- For i.i.d Gaussian sources
- We showed similar results at high rate



  – 1-D nested quantization: 1.53 dB away from the theoretical limit
  – 2-D nested quantization: 1.36 dB away from the theoretical limit
  – SWC-TCQ: 0.2 dB away from the theoretical limit

The Wyner-Ziv Problem

- Lossy coding and noiseless channels



- Rate-distortion theory

$$R_X(D) = \inf_{E\{d(U,X)\} \le D} I(X;U)$$

- Wyner-Ziv rate-distortion function

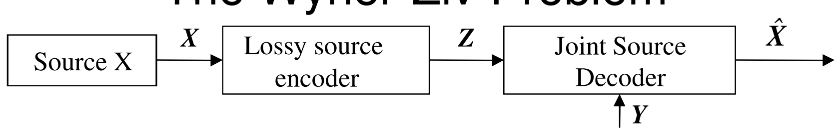
$$R^*_{WZ}(D) = \inf_{Y \to X \to Z;\, E\{d(X,\hat{X}(Z,Y))\} \le D} I(X;Z \mid Y)$$

- In general

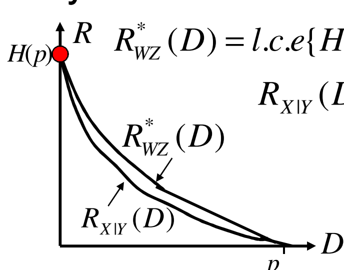
$$R^*_{WZ}(D) \ge R_{X|Y}(D) = \inf_{E\{d(U,X)\} \le D} I(X;U \mid Y)$$

- There is a rate loss with Wyner-Ziv coding (Zamir'96)
  - <.22 b/s for binary sources with Hamming distance
  - <.5 b/s for continuous sources with MSE measure

The Wyner-Ziv Problem



- Binary sources with Hamming distance

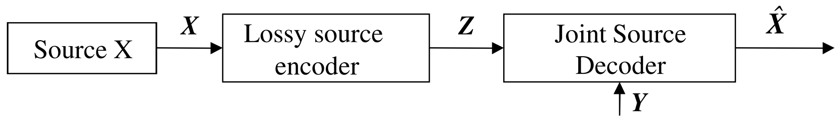


$$R^*_{WZ}(D) = l.c.e\{H(p*D) - H(D), (p,0)\}; 0 \le D \le p$$

$$R_{X|Y}(D) = H(p) - H(D)$$

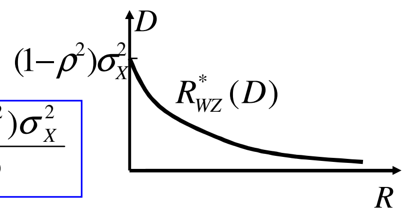
  - Rate loss with separate encoding in this case
  - When D=0, it degenerates to the Slepian-Wolf problem

The Wyner-Ziv Problem



- Joint Gaussian sources with MSE measure

$$\Lambda = \begin{bmatrix} \sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_X\sigma_Y & \sigma_Y^2 \end{bmatrix}$$



$$\boxed{R_{WZ}^*(D) = R_{X|Y}(D) = \frac{1}{2}\log_+ \frac{(1-\rho^2)\sigma_X^2}{D}}$$

  – Wyner-Ziv coding in this case suffers no loss!
  – This case is of special interest because images and video sources can be modeled as jointly Gaussian (after mean subtraction)

Wyner-Ziv Coding

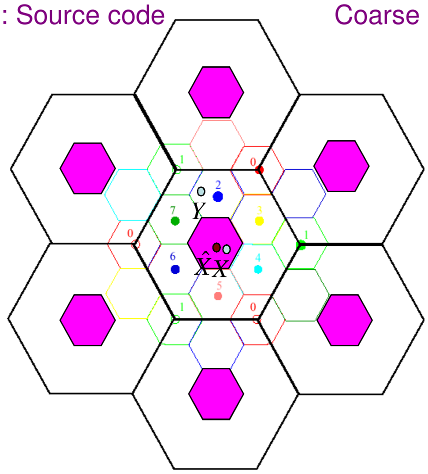
- **Binary sources with Hamming distance**
  – Zamir & Shamai'98 outlined the coding scheme based on nested linear codes
  – We have the only practical code design (ICIP'03)
- **Jointly Gaussian sources with MSE**
  – Zamir et al'98, Zamir et al'02: Suggested the use of nested lattice codes/quantization
  – Pradhan & Ramchandran'99: DISCUS (TCQ+TCM)
  – Servetto'00: Explicit nested lattice construction
  – Wang&Orchard'01: TCQ+trellis code
  – Effros et al'01: Side info may be coded
  – Chou, Pradhan & Ramchandran'03, TCQ+turbo code

The Quadratic Gaussian Case

- Nested lattice quantization (Zamir et al.'02)

Fine lattice: Source code

Coarse lattice: Channel code

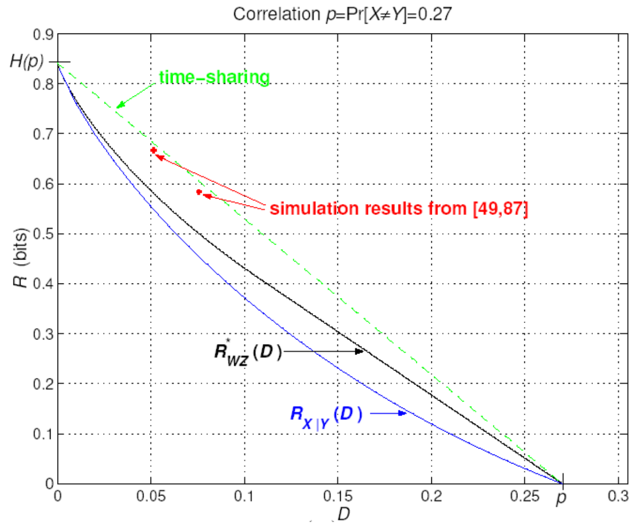


Our Work on Wyner-Ziv Coding

- For binary symmetric sources
  – Nested convolutional/turbo code design (ICIP'03)
- For i.i.d. Gaussian sources
  – Nested lattice quantization (SSP Workshop'03)
  – Nested quantization + Slepian-Wolf coding (SSP Workshop'03 & DCC'04)
  – TCQ and LDPC coding (Asilomar'03)
- For Gauss-Markov sources
  – Conditional KLT + nested quantization + Slepian-Wolf coding (SSP Workshop'03)
- Successive Wyner-Ziv coding
  – Theory and code design (DCC'04)
  – Layered Wyner-Ziv video coding (VCIP'04)

The Binary Wyner-Ziv Problem

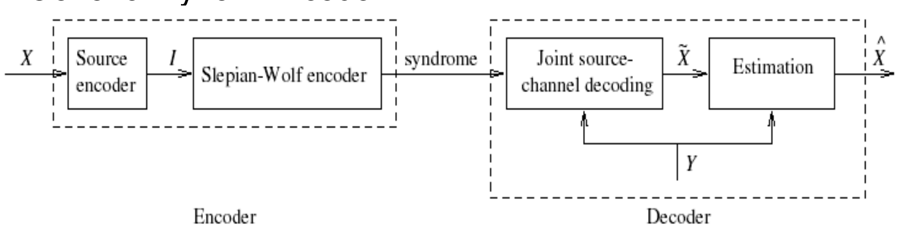
- Source correlation modeled as BSC with p=0.27



(ICIP'03)

The Quadratic Gaussian Case

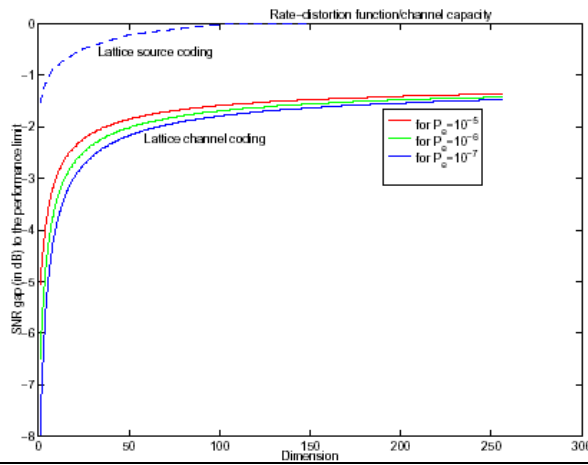
- Recall that there is no rate loss in this case!
- Generic Wyner-Ziv coder



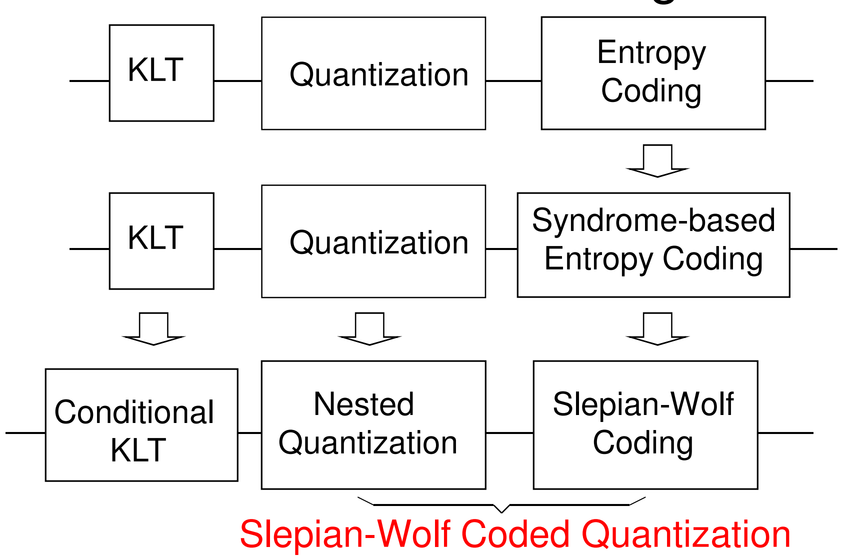
- A source-channel coding problem
  - Quantization loss due to source coding
  - Binning loss due to channel coding
- Lesson learned: Separate source-channel coding, no nesting
- Estimation of X based on quantized X and Y helps at low rate

The Quadratic Gaussian Case

- To reach the Wyner-Ziv limit, we need
  - Limit-approaching source and channel codes



From Classic Source Coding to DSC



The Quadratic Gaussian Case

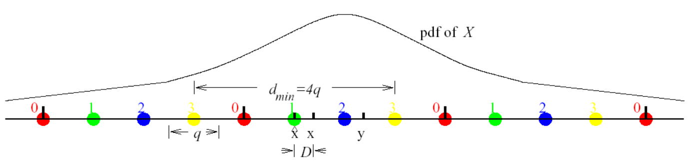
- High-rate performance of SWCQ
- Theorem 1: Assuming ideal Slepian-Wolf coding, SWCQ performs the same as classic entropy-coded quantization in terms of the gap to the respective D-R function.

High-rate classic source coding — High-rate Wyner-Ziv coding

	Gap to $D_X(R)$		Gap to $D^*_{WZ}(R)$
ECSQ	1.53 dB	SWC-SQ	1.53 dB
ECLQ (2-D)	1.36 dB	SWC-LQ	1.36 dB
ECTCQ256	0.20 dB	SWC-TCQ	0.20 dB

The Quadratic Gaussian Case

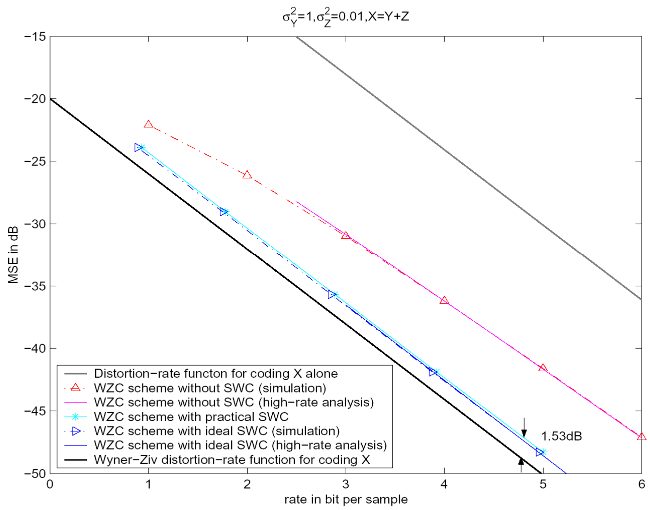
- SWC-NQ: the 1-D case (similar in the 2-D case)
- SC and CC components
  - Scalar quantization + coset channel code



- X first quantized w.r.t. the fine SC (with Q loss)
- Bin index in the coarse CC containing X is coded
- With the coded bin index, the decoder finds in the bin the codeword closest to the side information Y as the best estimate of X (binning loss)
- Best q searched to minimize Ds+Dc

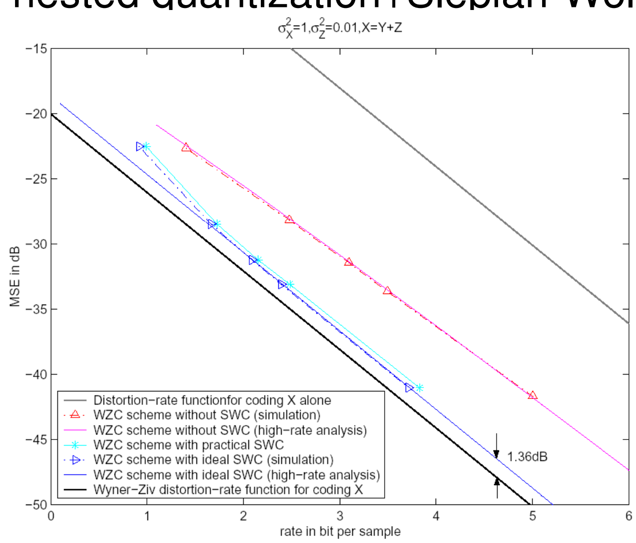
Wyner-Ziv Coding Results

- 1-D nested quantization+Slepian-Wolf coding



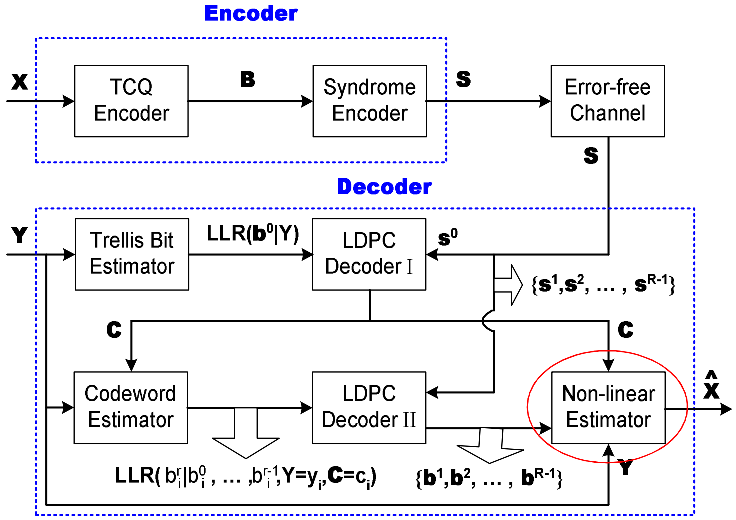
Wyner-Ziv Coding Results

- 2-D nested quantization+Slepian-Wolf coding

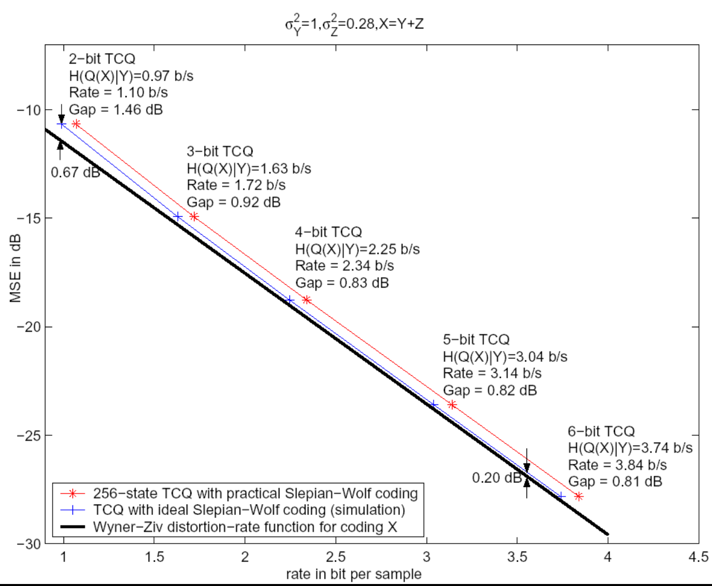


The Quadratic Gaussian Case

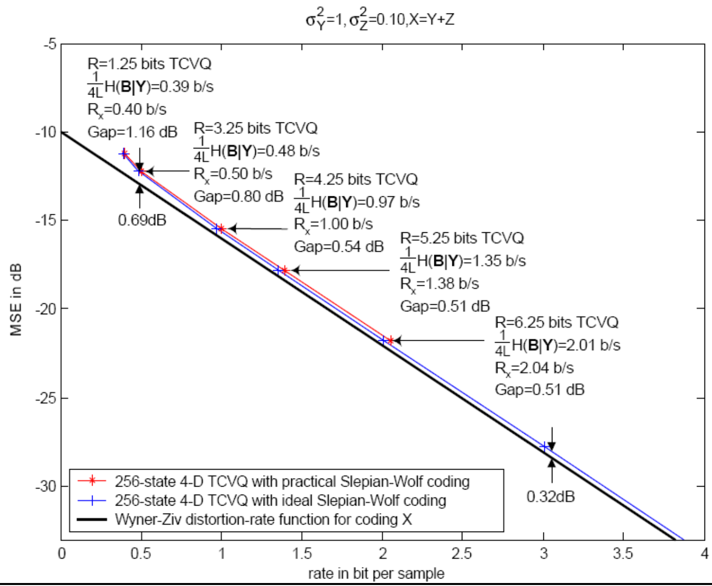
- SWC-TCQ: TCQ + LDPC codes + optimal estimation



Simulation results with TCQ



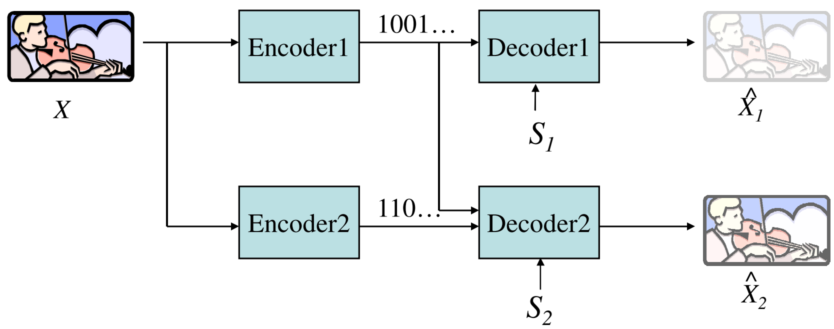
Simulation results with 4-D TCVQ



The Quadratic Gaussian Case (based on practical designs)

- Comparison
  - DISCUS (Pradhan & Ramchandran): 2-5 dB loss
  - Turbo+trellis (Chou, Pradhan & Ramchandran): 1.3 dB loss at 1 b/s
  - SWC-TCQ: 0.66 dB loss at 1 b/s
    0.44 dB loss at higher rates
- We are approaching the theoretical performance limit of Wyner-Ziv coding!

Successive Wyner-Ziv Coding



We only consider the case when $S_1 = S_2$

Successive Wyner-Ziv Coding

- Successful refinement with side information
  - Generalization of Equitz & Cover'91
- (X,Y) is successively refinable if for any $D_1 > D_2$, we can find a code $(R(D_1), D_1, Y; R(D_2) - R(D_1), D_2, Y)$
- Examples
  - Jointly Gaussian source with MSE distortion measure
    - Important result in practical (e.g., video) applications
  - Doubly-symmetric binary source with the Hamming distortion measure
- Certain sources that are not successively refinable alone can be successively refinable with the help of the side information

Successive Wyner-Ziv Coding

- Recall: no rate loss in Wyner-Ziv coding for
  - Quadratic Gaussian source
- Generalization of no rate loss by Pradhan et al.
  - X=Y+Z as long as Z is Gaussian
- We show such source X is successively refinable in Wyner-Ziv coding
- Performed layered Wyner-Ziv code design
  - Nested scalar quantization
  - Bit-plane based LDPC code for Slepian-Wolf coding
  - Applied to layered Wyner-Ziv video coding (more later)

Tutorial Outline

I. Background
- Slepian-Wolf coding
- Wyner-Ziv coding
- Distributed source-channel coding
- Multiterminal source coding

II. DVC overview (start from conventional video coding)
- Work done by other groups
- Layered Wyner-Ziv video coding
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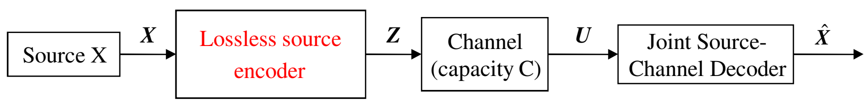
III. DVC roadmap
- Scalable Slepian-Wolf coding
- Correlation modeling and universal Slepian-Wolf coding
- Practical low-complexity and high-efficiency DVC

Classic Source-channel Coding

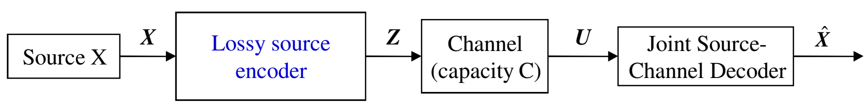
- Lossless source coding with noisy channel



  - Separation Theorem for source-channel coding

$$R_1 \geq H(X)/C$$

- Case 2: Lossy source coding with noisy channel

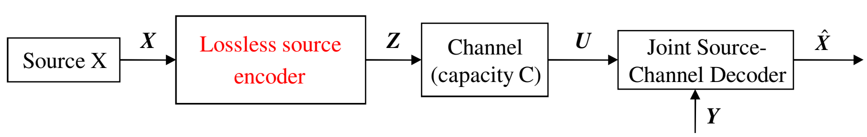


  - Separation Theorem for lossy source-channel coding:

$$R_1 \geq R(D)/C$$

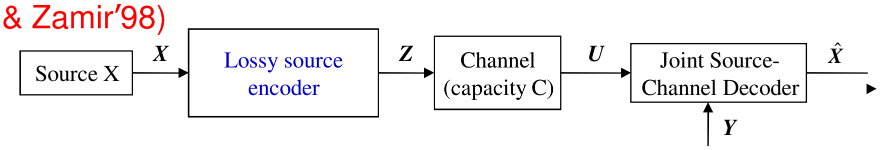
Distributed Source-channel Coding

- Slepian-Wolf problem with noisy channel (Shamai & Verdu'95)



  - Separation Theorem for source-channel coding with side information: $R_1 \geq H(X \mid Y)/C$

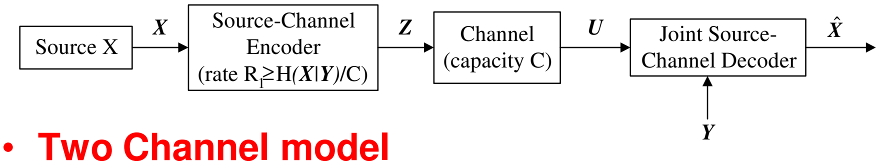
- Case 2: Wyner-Ziv problem with noisy channel (Shamai, Verdu & Zamir'98)



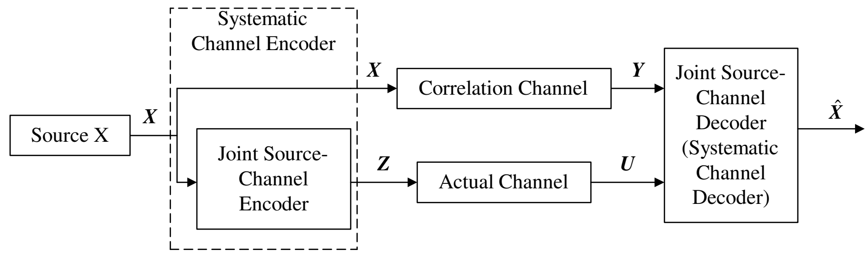
  - Separation Theorem for lossy source-channel coding with side information:

$$R_1 \geq R_{WZ}^{*}(D)/C$$

Distributed Source-channel Coding



- **Two Channel model**

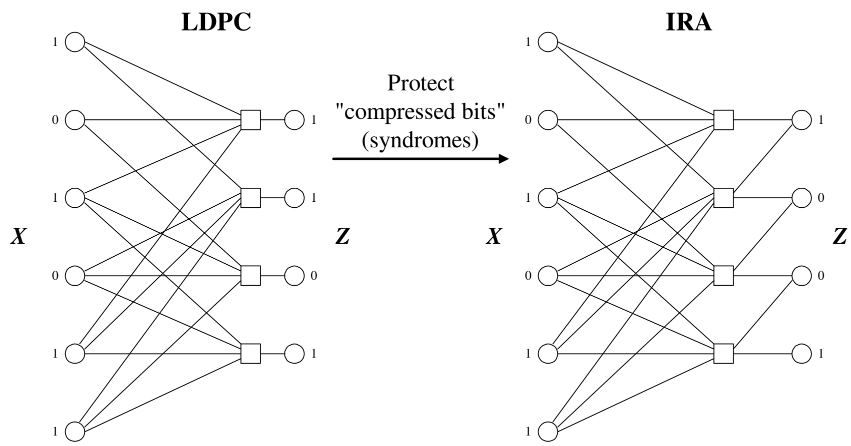


- **Use of systematic channel/IRA codes**
  - ***Different channel conditions for systematic and parity part***

Parity-based Approach for Distributed JSCC

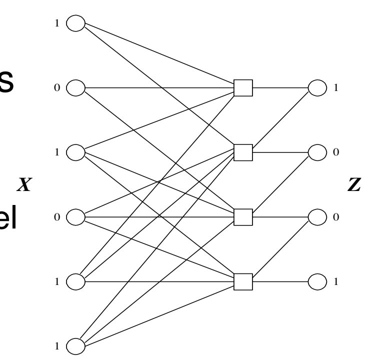
- Syndrome-based approach for Slepian-Wolf coding
  - (n_s, k_s) code, n_s-bit input X, (n_s-k_s)-bit output syndrome S
  - Compression ratio is n_s : n_s-k_s =1 : H(X|Y)
  - S=XH; H has size n_sx(n_s-k_s); code rate k_s/n_s=1-H(X|Y)
  - X & Y are related by a correlation channel, n_s bits involved
- Parity-based approach for distributed JSCC
  - (n_p, k_p) code, k_p-bit input X, (n_p-k_p)-bit output parity vector C
  - Compression ratio is k_p : n_p-k_p = n_s : n_s-k_s =1 : H(X|Y)
    - With K_p= n_s; n_p=2n_s-k_s to establish equivalence in the Slepian-Wolf case
  - C=XP with P=H; code rate k_p/n_p=1/(1+H(X|Y))
    - Virtual correlation channel between X & Y; n_s bits involved
    - Actual noisy channel that C goes through; n_s-k_s bits involved

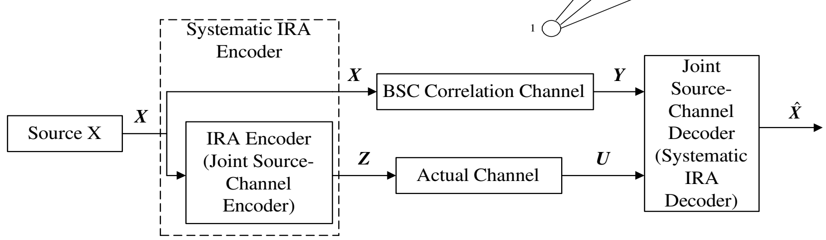
IRA Codes for Distributed JSCC



IRA Code Design for DJSCC

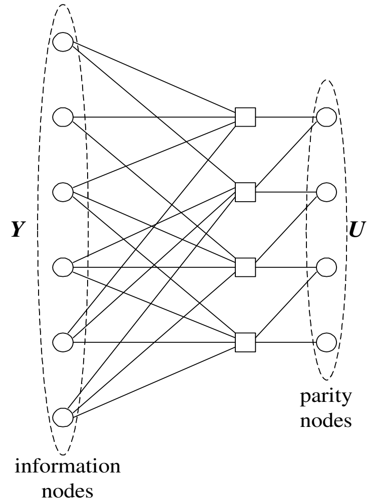
- Advantage
  - Allow design of good codes with different channel conditions for *X* and *Z*
    - ***X*** → BSC correlation channel
    - ***Z*** → BSC, AWGN or fading channel





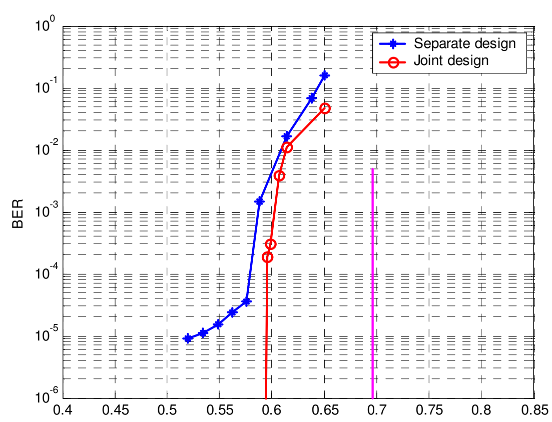
IRA Codes: Decoding

- Use of ***conventional*** iterative algorithm
  - *Initialization*
    - Side information ***Y***
      - **Information node input**
    - Actual channel output ***U***
      - **Parity node input**
  - **No other modification in the iterative decoding algorithm**



Distributed JSCC vs. Separate Coding

- Joint design: Parity-based approach with IRA codes
- Separate design: Slepian-Wolf coding + FEC



Correlation channel: BSC with c.o.p = p

Actual noisy channel: AWGN channel with -5.02dB SNR

Comparison with turbo codes (Zhu et al.)

- Source-channel code rate R_1=2
  - no compression, factor of 2 expansion
  - Gap from theoretical limit in dB (BER$\leq 10^{-5}$)

	AWGN channel		Rayleigh fading	
$Pr[X_i \neq Y_i]$	turbo	IRA	turbo	IRA
0.3	0.87	0.77	1.16	0.95
0.2	0.87	0.83	1.11	1.36
0.1	1.05	0.78	1.15	1.10

- Distributed JSCC of video (more later)

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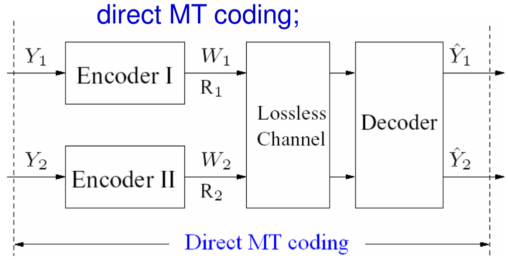
Multiterminal (MT) Source Coding

- **Definition**
  - Separate lossy encoding and joint decoding of multiple correlated sources.
  - Two cases:

direct MT coding;

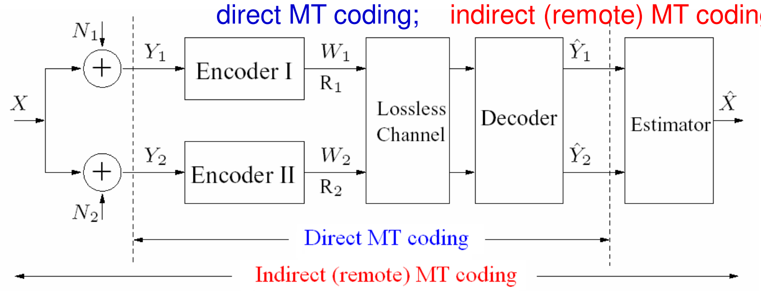


  - Correlated sources Y_1 & Y_2
  - Transmission rates (R_1, R_2)
  - Two distortion constraints $E[d(Y_1, \hat{Y}_1)] \leq D_1, \quad E[d(Y_2, \hat{Y}_2)] \leq D_2$

Multiterminal (MT) Source Coding

- **Definition**
  - Separate lossy encoding and joint decoding of multiple correlated sources.
  - Two cases:

direct MT coding; indirect (remote) MT coding



  - Y_1 & Y_2- Noisy observations of the source X
  - Transmission rates (R_1, R_2)
  - Only one distortion constraint $E[d(X, \hat{X})] \leq D$

Theoretical Limits for Direct MT Coding

(Berger/Tung'77)

Inner bounds: Outer bounds:

$R_1 \geq I(Y_1Y_2;Z_1|Z_2)$,
$R_2 \geq I(Y_1Y_2;Z_2|Z_1)$,
$R_1+R_2 \geq I(Y_1Y_2;Z_1Z_2)$,

where Z_1 and Z_2 are auxiliary random variables such that:
$Z_1 \to Y_1 \to Y_2 \to Z_2$, and $(Y_1,Y_2)=g(Z_1, Z_2)$ is decoder estimation function

where Z_1 and Z_2 are auxiliary random variables such that:
$Z_1 \to Y_1 \to Y_2$ and $Z_2 \to Y_2 \to Y_1$

Quadratic Gaussian Direct MT Coding

(Two Sources/Encoders)

- **Definition**
  - (Y_1, Y_2) are zero-mean jointly Gaussian sources with variances $(\sigma_{y1}^2, \sigma_{y2}^2)$ and correlation coefficient $\rho = \frac{E[Y_1Y_2]}{\sigma_{y1}\sigma_{y2}}$
- **Inner and outer bounds** (Oohama'98)

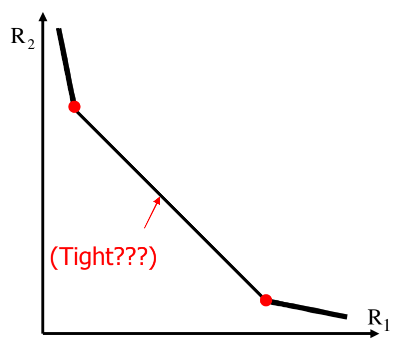
Inner bounds

$$R_1 \geq \frac{1}{2}\log[\frac{\sigma_{y_1}^2}{D_1}(1-\rho^2+\rho^2 2^{-2R_2})],$$

$$R_2 \geq \frac{1}{2}\log[\frac{\sigma_{y_2}^2}{D_2}(1-\rho^2+\rho^2 2^{-2R_1})],$$

$$R_1+R_2 \geq \frac{1}{2}\log[(1-\rho^2)\frac{\beta_{max}\sigma_{y_1}^2\sigma_{y_2}^2}{2D_1D_2}],$$

$$\beta_{max} = 1+\sqrt{1+\frac{4\rho^2 D_1D_2}{(1-\rho^2)^2\sigma_{y_1}^2\sigma_{y_2}^2}},$$



Quadratic Gaussian Direct MT Coding

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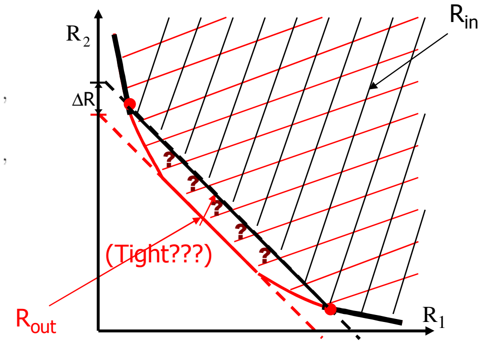
- **Inner and outer bounds** (Oohama `98)

Outer bounds

$$R_1 \geq \frac{1}{2}\log[\frac{\sigma_{y_1}^2}{D_1}(1-\rho^2+\rho^2 2^{-2R_2})],$$

$$R_2 \geq \frac{1}{2}\log[\frac{\sigma_{y_2}^2}{D_2}(1-\rho^2+\rho^2 2^{-2R_1})],$$

$$R_1 + R_2 \geq \frac{1}{2}\log[(1-\rho^2)\frac{\sigma_{y_1}^2\sigma_{y_2}^2}{D_1 D_2}].$$

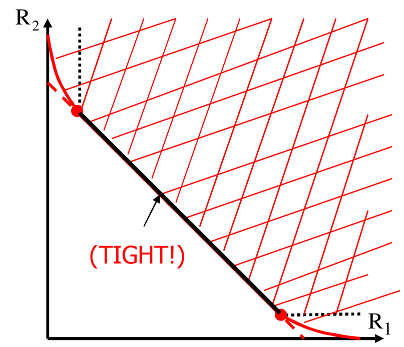


Quadratic Gaussian Direct MT Coding

(Two Sources/Encoders)

- **Berger-Tung inner bound is tight in the two-terminal case (Wagner et al. '05)**
- **Vector quantization followed by Slepian-Wolf coding is optimal**
- **The rate region still unknown for more than two terminals!!!**

Direct setting



Theoretical Limits of Indirect MT Coding

(Yamamoto/Itoh'80)

Inner bounds: Outer bounds:

$R_1 \geq I(Y_1Y_2;Z_1|Z_2)$,
$R_2 \geq I(Y_1Y_2;Z_2|Z_1)$,
$R_1+R_2 \geq I(Y_1Y_2;Z_1Z_2)$,

where Z_1 and Z_2 are auxiliary random variables such that: $Z_1 \to Y_1 \to Y_2 \to Z_2$, and $X=g(Z_1, Z_2)$ is decoder estimation function

where Z_1 and Z_2 are auxiliary random variables such that: $Z_1 \to Y_1 \to Y_2$ and $Z_2 \to Y_2 \to Y_1$

Quadratic Gaussian Indirect MT Coding

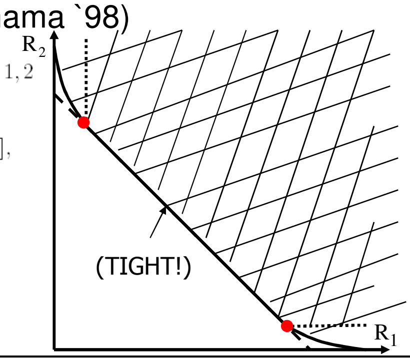
(Oohama'98, Chen et al.'04)

- **Definition**
  - X, N_1, N_2 are zero-mean mutually independent Gaussian random variables with variances σ_x^2, σ_n^2 and σ_n^2.
  - Two noisy observations: $Y_1 = X + N_1; \quad Y_2 = X + N_2;$
- **Inner sum rate bound** (Oohama `98)

$$R_i \geq \frac{1}{2}\log^+\left[\frac{2\sigma_x^2}{\sigma_x^2+D}\cdot\left(1-\frac{\sigma_n^2(\sigma_x^2-D)}{2\sigma_x^2 D}\right)^{-1}\right], i=1,2$$

$$R_1+R_2 \geq \frac{1}{2}\log^+\left[\frac{\sigma_x^2}{D}\cdot\left(1-\frac{\sigma_n^2(\sigma_x^2-D)}{2\sigma_x^2 D}\right)^{-2}\right],$$

This inner bound is TIGHT!
(Oohamma'99
Prabhakaran,Tse, & Ramchandran'04)

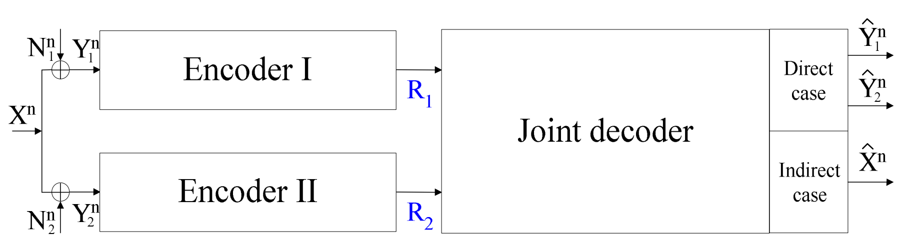


MT Source Code Design

- Large body of theoretical work, few practical code designs
- Past works on code design for indirect setting
  - Flynn & Gray'88: index reuse
  - Pradhan & Ramchandran'03:
    - Scalar quantization + trellis code
  - Our work: (DCC'04 & DCC'05)
    - Classical source coding + Wyner-Ziv coding
    - TCQ for SC + Slepian-Wolf coded TCQ for Wyner-Ziv
    - 0.15 b/s gap to the inner bound
- Past works on code design for direct setting
  - None

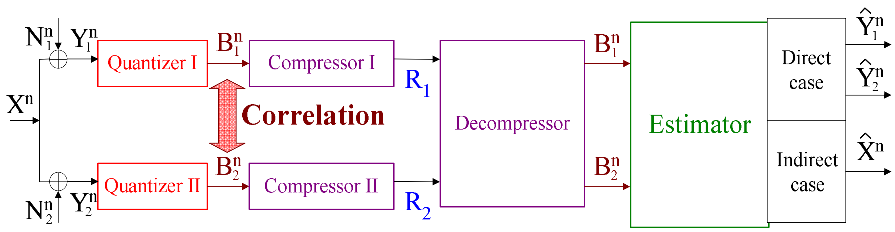
Proposed Code Design (Slepian-Wolf Coded Quantization)

- ***Main idea: Slepian-Wolf coding after quantization***



Proposed Code Design (Slepian-Wolf Coded Quantization)

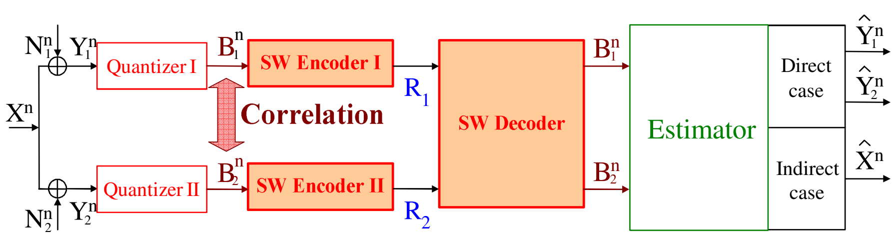
- **Main idea: Slepian-Wolf coding after quantization**



- Quantization + Compression
- Correlation between $B_1^n = Q(Y_1^n)$ and $B_2^n = Q(Y_2^n)$

Proposed Code Design (Slepian-Wolf Coded Quantization)

- **Main idea: Slepian-Wolf coding after quantization**



- Quantization + Compression
- Correlation between $B_1^n = Q(Y_1^n)$ and $B_2^n = Q(Y_2^n)$
- Compression $\rightarrow$ SW coding
- Achieving sum-rate of $H(B_1^n, B_2^n)$

Proposed Code Design
(Slepian-Wolf Coded Quantization)

$$\textbf{Quantization} + \left\{\begin{array}{l}\textbf{Asymmetric SW coding}\\ \\ \textbf{Symmetric SW coding}\end{array}\right\} = \left\{\begin{array}{l}\textbf{Asymmetric SWCQ}\\ \\ \textbf{Symmetric SWCQ}\end{array}\right.$$

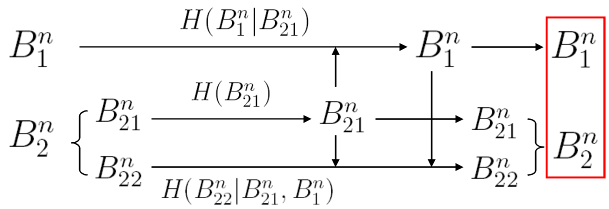
- Asymmetric SWCQ
  - Easily achieves the corner points of the inner bounds
    - Our work (DCC′04) for indirect MT coding: 0.15b/s loss

$$H(B_1^n, B_2^n) = H(B_1^n) + H(B_2^n|B_1^n)$$

  - With time sharing it can achieve any point
  - Using source splitting to achieve any point
- Symmetric SWCQ
  - Achieves any point on the inner bounds

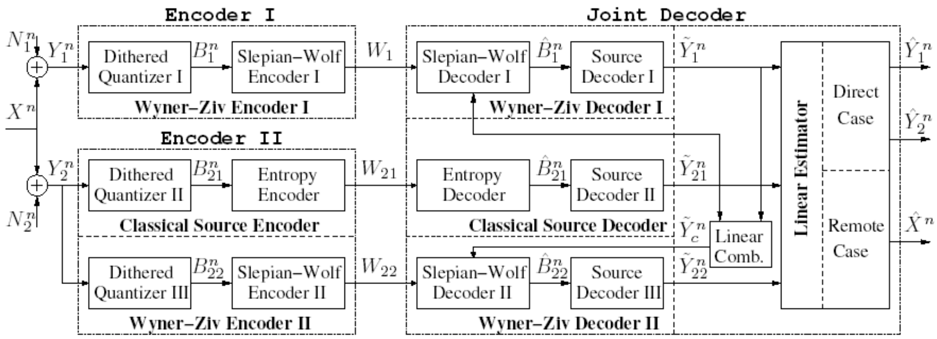
Asymmetric SWCQ Based on Source Splitting

- Motivation
  - To achieve any point on theoretical bounds
- Source splitting
  - Introduced by Rimoldi and Urbanke for SW coding;
  - Main idea:



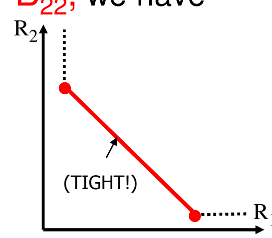
Asymmetric SWCQ Based on Source Splitting

- 3 steps for MT coding
  - Classical source coding for the first source;
  - Wyner-Ziv coding for the second given the decoded first source as side information
  - Using the two decoded sources as side information, additional rate is spent on the first source in a second Wyner-Ziv coding step.

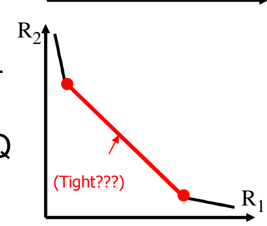


Asymmetric SWCQ Based on Source Splitting

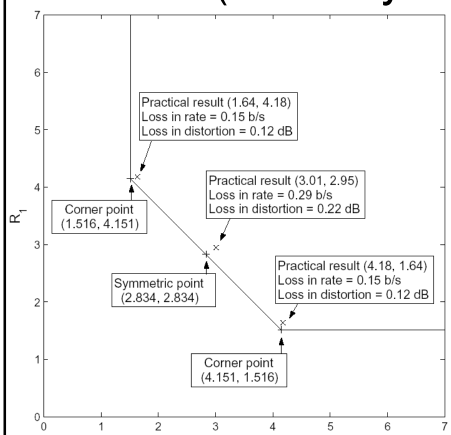
- Given ideal source coding, ideal SW coding, and $B_1 \to Y_1 \to Y_2 \to (B_{21}, B_{22})$, $B_{21} \to Y_2 \to B_{22}$, we have
- Theorem 2:
  Any rate pair (R_1,R_2) on the sum-rate bound of the indirect MT problem is achievable with our asymmetric SWCQ design.



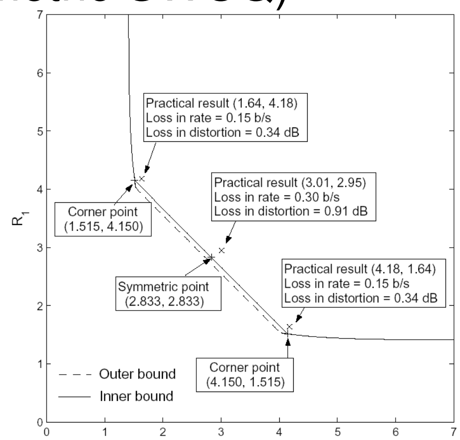
- Theorem 3:
  Any rate pair (R_1,R_2) on the inner sum-rate bound of the direct MT problem is achievable with our asymmetric SWCQ design.



Simulation Results (with Asymmetric SWCQ)

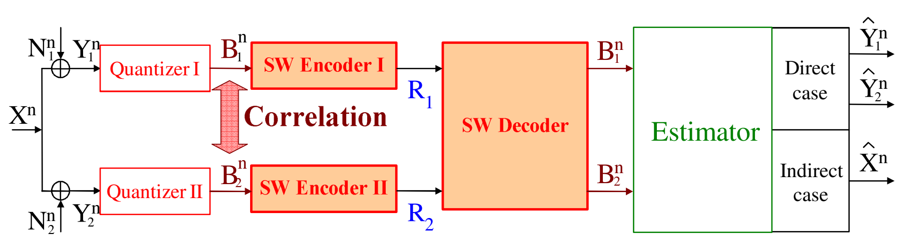


Experimental results together with the sum rate bound for the indirect MT problem. Target distortion *D*=-21.83 dB and CSNR=20 dB.



Experimental results together with the inner and outer bounds for the direct MT problem. Target distortions are $D_2=D_1=-25.54$ dB and $\rho=0.9901$.

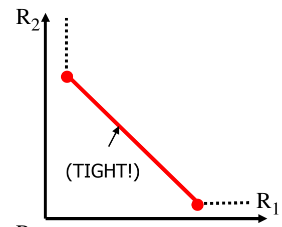
Symmetric SWCQ



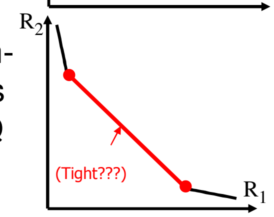
- TCQ + symmetric Slepian-Wolf compression
  - Based on channel code partitioning
- Correlation between $B_1^n = Q(Y_1^n)$ and $B_2^n = Q(Y_2^n)$
- Achieving sum-rate of $H(B_1^n, B_2^n)$

Symmetric SWCQ -- Theorems

- Given ideal source coding, ideal SW coding, and Markov chain $B_1 \to Y_1 \to Y_2 \to B_2$, we have
- Theorem 4:
  Any rate pair (R_1,R_2) on the sum-rate bound of the indirect MT problem is achievable with our symmetric SWCQ design.



- Theorem 5:
  Any rate pair (R_1,R_2) on the inner sum-rate bound of the direct MT problem is achievable with our symmetric SWCQ design.



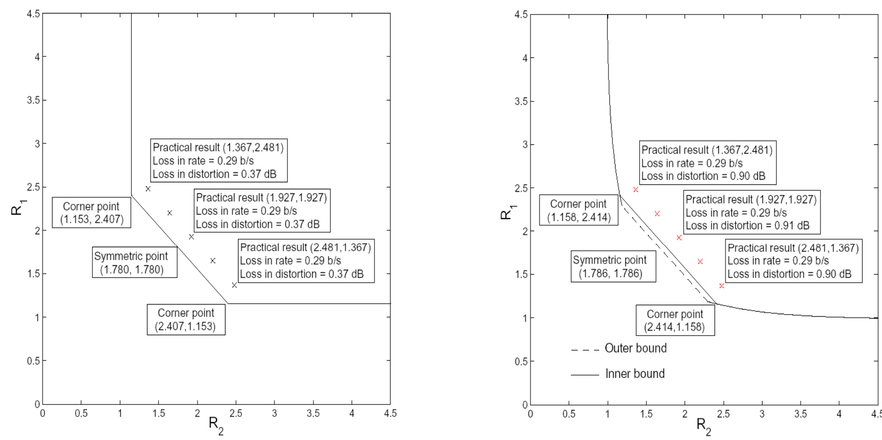
Simulation Results (with symmetric SWCQ)

- q=0.38, ρ =0.941, D=-13.16dB, $D_1=D_2$=-15.32dB
- Inner sum-rate bound R_{min}=3.56 b/s
- Joint entropy $H(B_1, B_2)$

Bitplane	$H(B_1, B_2)$	$\frac{1}{n}H(U_1^n, V_1^n)$	$H(U_2, V_2 \mid \mathcal{M}_1)$	$H(U_3, V_3 \mid \mathcal{M}_2)$
Theoretical value	3.699	1.979	1.274	0.446
Practical results	3.853	2.000	1.322	0.531
Loss	0.154	0.021	0.048	0.085

- Inherent loss 3.699-3.56=0.14 b/s
  - From source coding
- Trellis bit plane: 0.021 b/s loss
- Turbo code based design
  - Block length n=5*10^5 BER<10^{-6}
  - Rate-2/3 turbo code for U_2V_2 – 0.048 b/s loss
  - Rate-26/27 turbo code for U_3V_3 – 0.085 b/s loss
- Overall loss: 3.85-3.56 = 0.29 b/s

Simulation Results (with Asymmetric SWCQ)



(a) Indirect MT: $D = -13.16$ dB, CSNR = 12.05 dB

(b) Direct MT: $D_1 = D_2 = -15.32$ dB, ρ=0.94

Summary on MT Source Code Designs

- A general SWCQ framework for both direct and indirect MT coding problems
- Two practical code designs: symmetric and asymmetric SWCQ
- Assuming ideal source coding, ideal SW coding, and the Markov chains, each design can achieve any point on the inner bound of the rate regions for both the quadratic Gaussian direct and indirect MT problems
- Practical results are very close to the theoretical limits: 0.29 b/s loss in rate, 0.90 dB loss in distortion
- Applications in MT video coding (more later)

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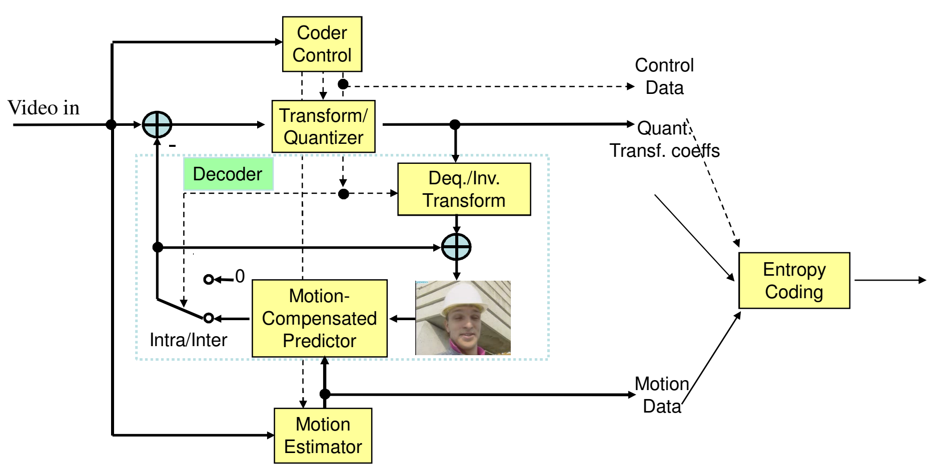
- Practical low-complexity and high-efficiency DVC

Background on Video Coding

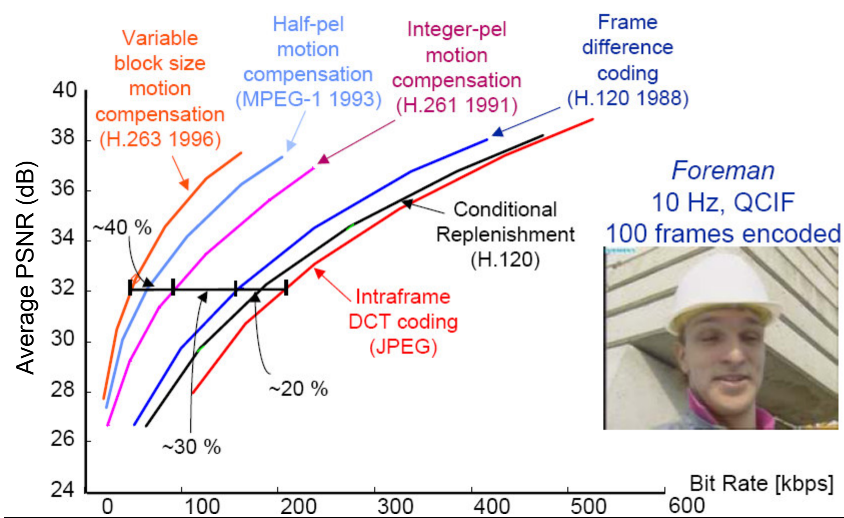
- Standard motion-compensated video coding



Standards: H.261, MPEG-1, MPEG-2, H.263, MPEG-4, H.264/AVC

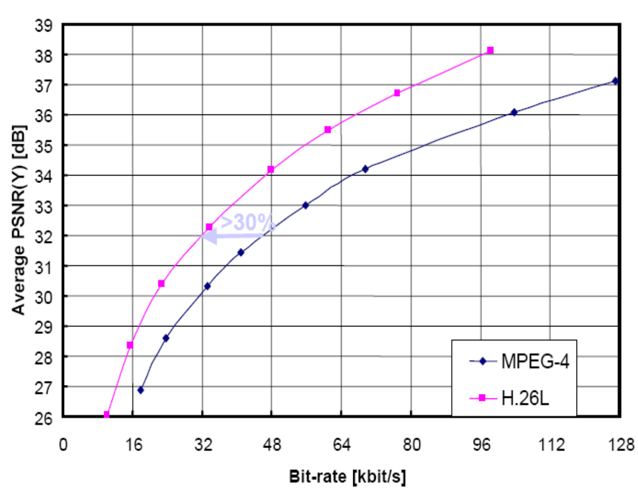
Background on Video Coding

- Performance improvement (H.261-> MPGE-1-> H.263)



Background on Video Coding

- Performance improvement (MPGE-4 -> H.264)

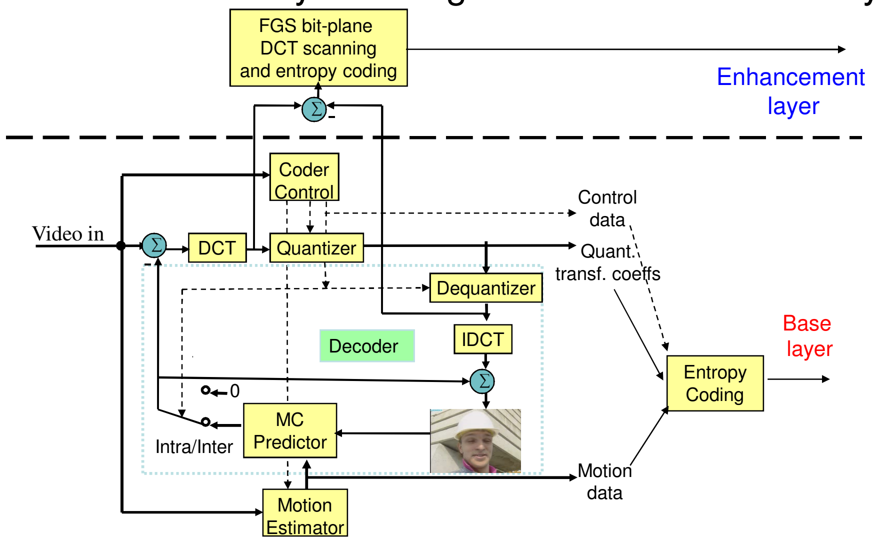


Foreman
10 Hz, QCIF

- H.264 achieves twice as much compression as MPEG-2 at the same quality

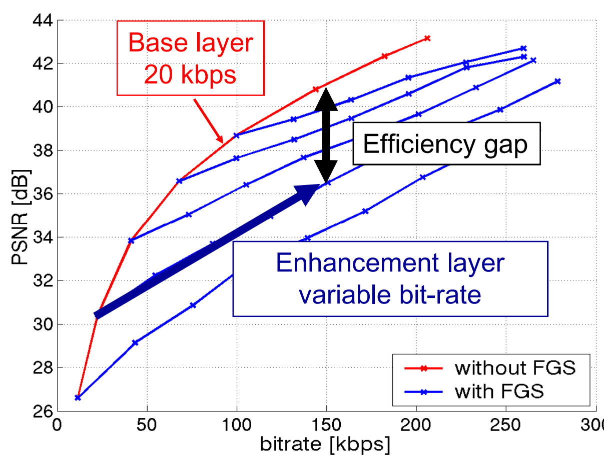
Background on Video Coding

- Standard base layer coding + FGS enhancement layer



Background on Video Coding

- H.264 with/without FGS coding

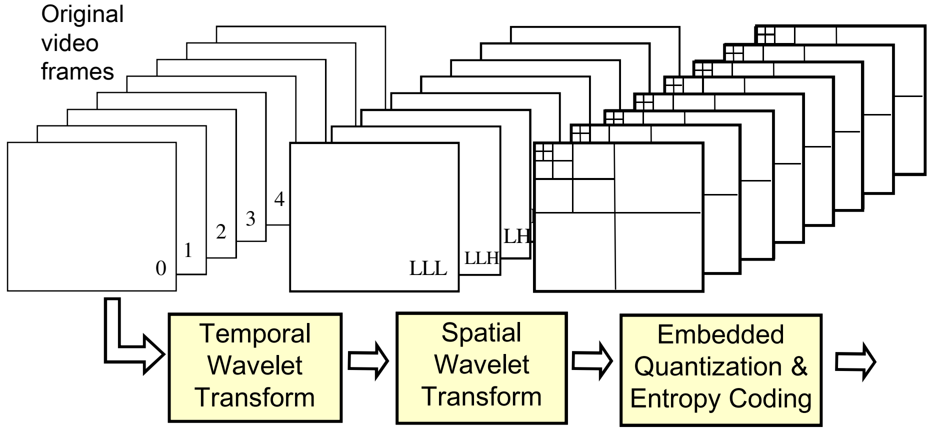


Foreman

5 Hz

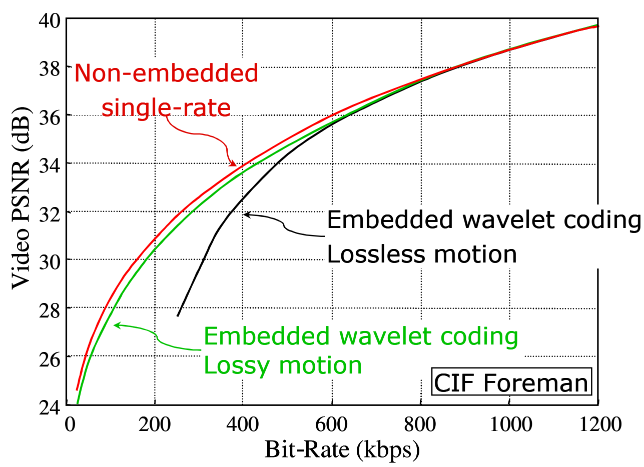
Background on Video Coding

- 3-D wavelet video coding (Woods,Taubman, et al)



Background on Video Coding

- Performance comparison (H.264,wavelet video coding)



Distributed Video Coding

- H.264/AVC
  - Achieves twice as much compression as the successful MPEG-2 at the same quality
  - Very difficult to have another factor of two improvement
- New applications (e.g., camera arrays) demand novel approaches
  - Theoretical foundation of distributed source coding laid 30+ years ago
  - Limit-approaching code designs for ideal sources devised in recent years
  - Time is ripe for distributed video coding (DVC)
- MPEG recently identified DVC as one of the future directions of video compression
  - Heavy research on DVC (US, Europe/DISCOVER, and China)

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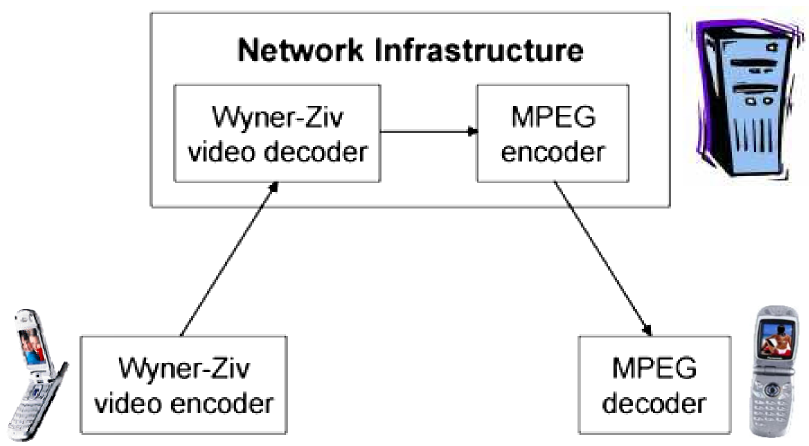
Distributed Video Coding

- Promising applications
  - Low-complexity wireless video



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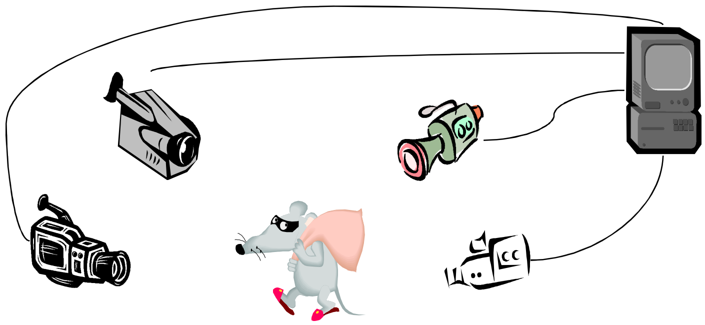
Distributed Video Coding

- Promising applications
  - Video surveillance and sensor networks



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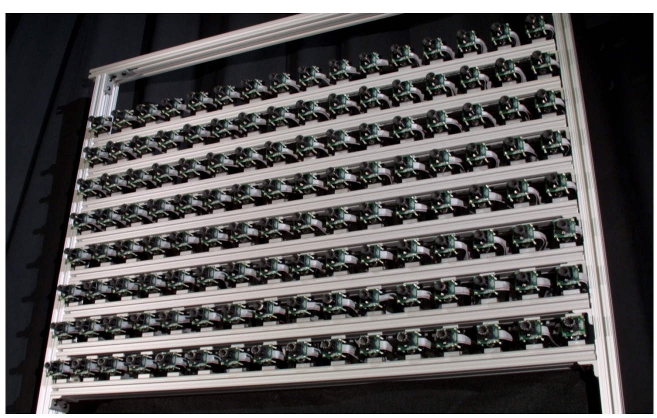
Distributed Video Coding

- Promising applications
  - Camera arrays (Stanford and Tsinghua)



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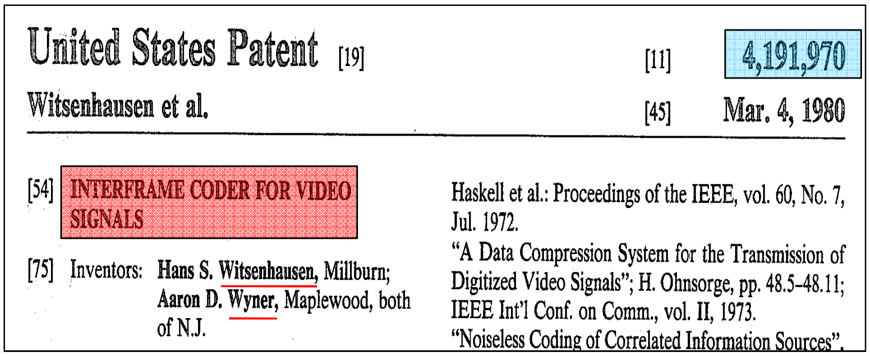
Distributed Video Coding

- The idea of DVC was first patented in 1980 by Witsenhausen and Wyner
  - US patent 4191970: Interfrace coder for video signas



United States Patent [19] [11] 4,191,970

Witsenhausen et al. [45] Mar. 4, 1980

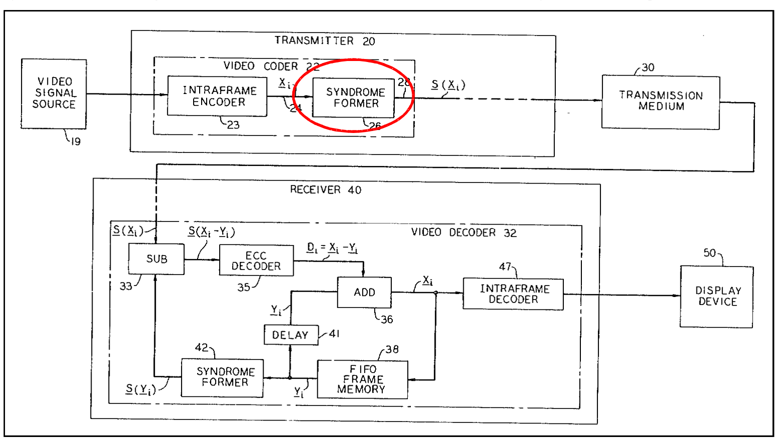
[54] INTERFRAME CODER FOR VIDEO SIGNALS

[75] Inventors: Hans S. Witsenhausen, Millburn; Aaron D. Wyner, Maplewood, both of N.J.

Haskell et al.: Proceedings of the IEEE, vol. 60, No. 7, Jul. 1972.
"A Data Compression System for the Transmission of Digitized Video Signals"; H. Ohnsorge, pp. 48.5–48.11; IEEE Int'l Conf. on Comm., vol. II, 1973.
"Noiseless Coding of Correlated Information Sources".

Distributed Video Coding

- Key drawing in Witsenhausen & Wyner's patent



- No practical implementation
  - First practical system: PRISM from Berkeley

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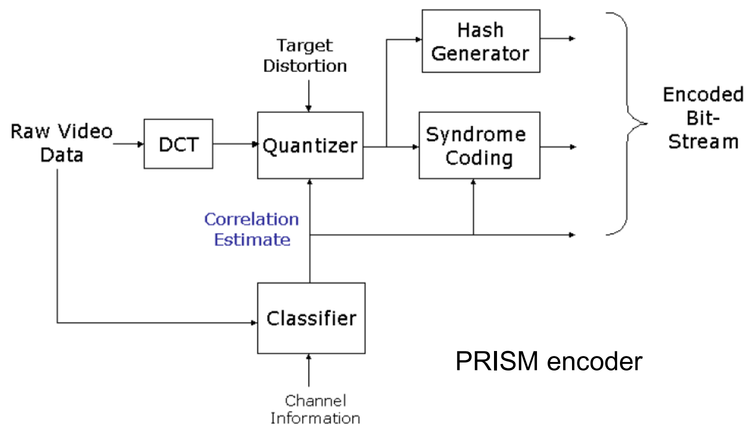
Distributed Video Coding

- Target at low-complexity encoding
  - PRISM (Ramchandran)
  - DCT-domain Wyner-Ziv video coding (Gorid)
- Layered Wyner-Ziv coding
  - Xiong, Ortega, Sehgal & Jagmohan, and Ramchandran
  - Others ?
- Target at error-robustness
  - Sehgal & Jagmohan, Xiong, Ramchandran, Girod
  - Others ?
- Focus on correlation estimation
  - Delp, DISCOVER team
- Multiterminal video coding
  - Xiong, Ramchandran, DISCOVER team, Microsoft, China

Distributed Video Coding

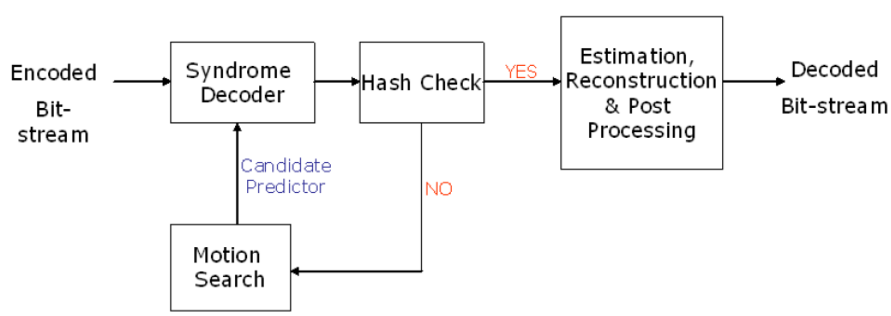
- PRISM in non-MC mode (Ramchandran)
  – Encoder relies on off-line training for correlation estimation
  – BCH-based syndrome coding and CRC-based hash



PRISM encoder

Distributed Video Coding

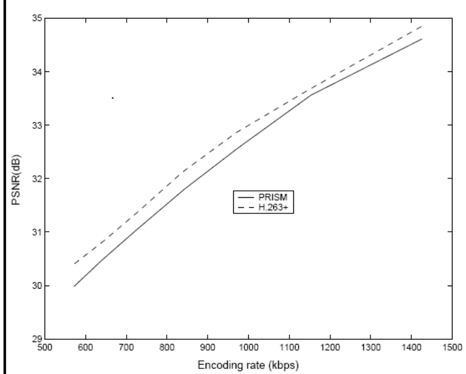
- PRISM in non-MC mode (Ramchandran)
  – Decoder performs motion search, syndrome decoding and hash check
  – Joint decoding involves estimation and post-processing



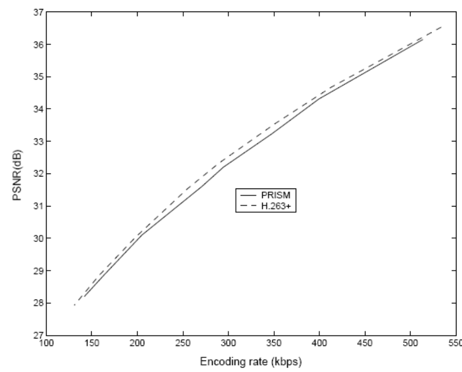
PRISM decoder

Distributed Video Coding

- PRISM in full-MC mode (Ramchandran)
  - Syndrome-based coding after MC
  - Performance close to that of H.263+



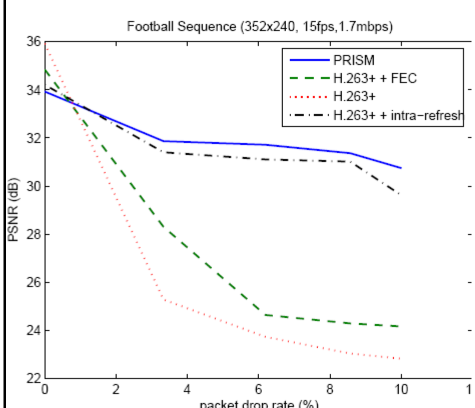
Football, 15 Hz

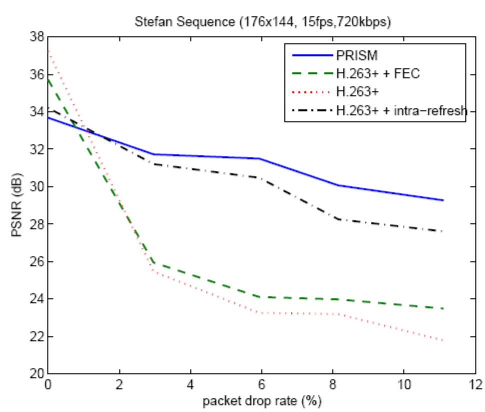


QCIF Stefan, 15 Hz

Distributed Video Coding

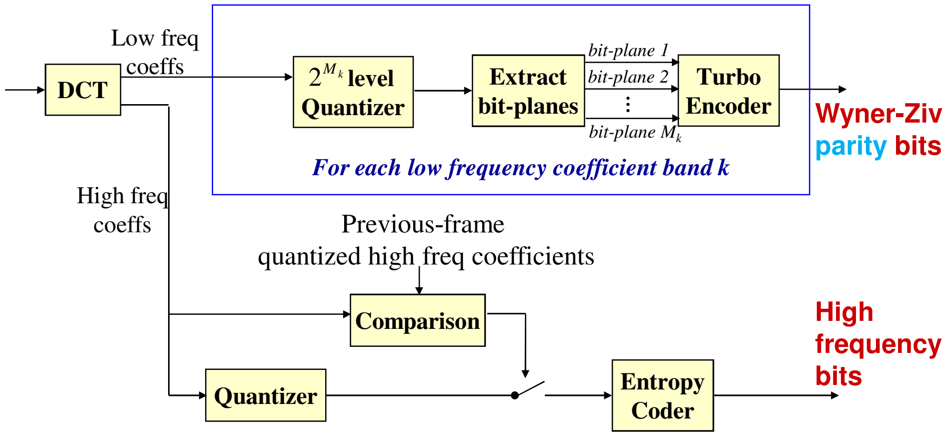
- PRISM in non-MC mode (Ranchandran)
  - Worse compression performance than H.263+
  - But more robust against transmision errors





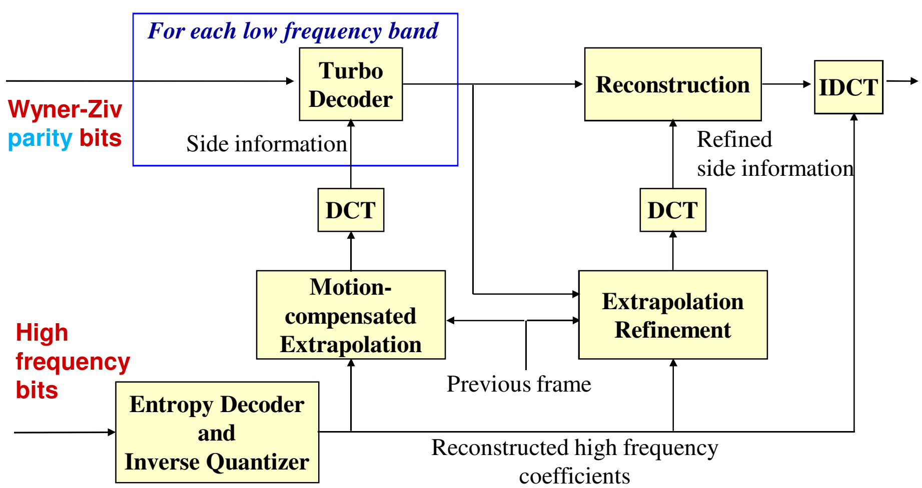
Distributed Video Coding

- DCT-domain Wyner-Ziv video encoder (Girod)



Distributed Video Coding

- DCT-domain Wyner-Ziv video decoder (Girod)



Distributed Video Coding

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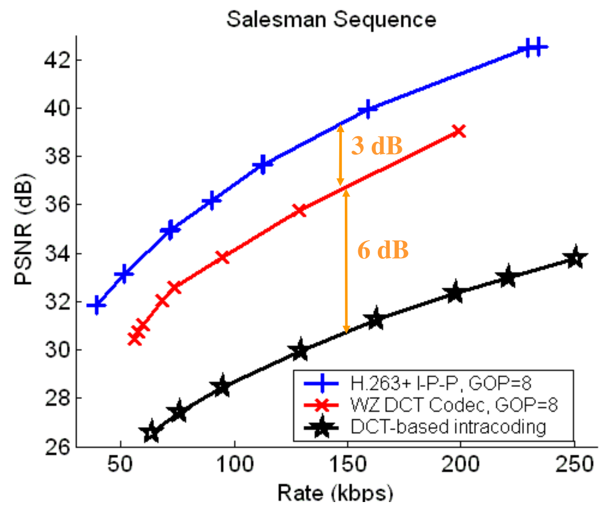
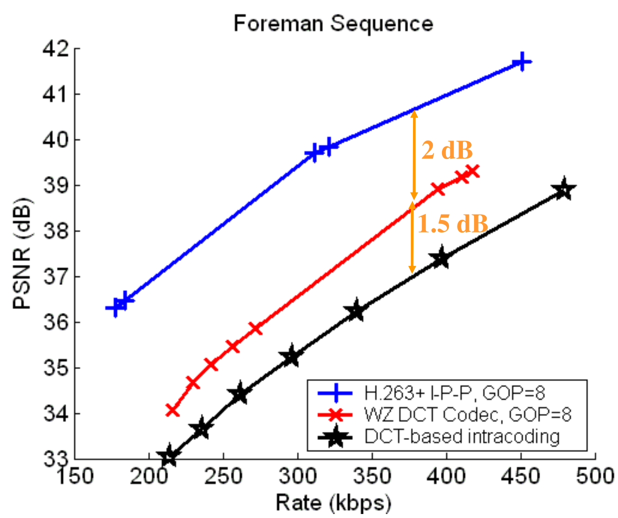


Distributed Video Coding

- DCT-domain Wyner-Ziv video coding (Girod)



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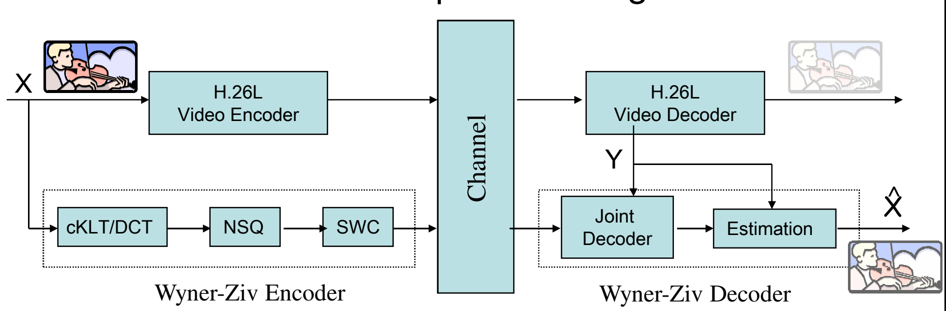
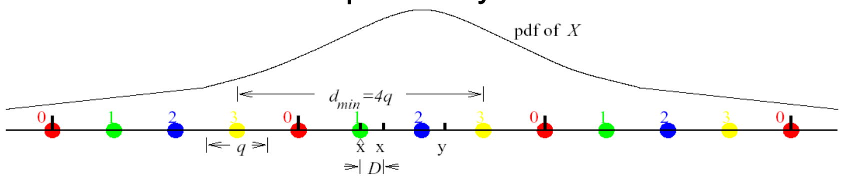
Layered Wyner-Ziv Video Coding

- H.26L based layer as decoder side information
- DCT as an approximation to the conditional KLT (Gastpar et al '03)
- Nested scalar quantization (NSQ)
- LDPC code based bit plane coding for SWC



Nested Scalar Quantization

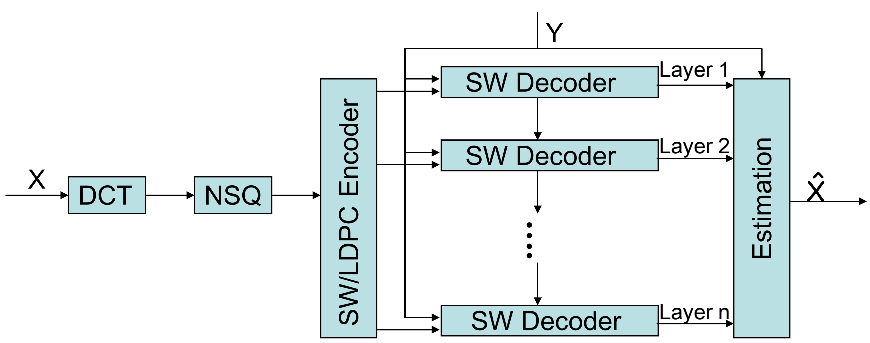
- NSQ is a binning process that partitions the input into cosets and outputs only the coset indices



- A coarse coset channel code nested in a fine uniform scalar quantizer
  - N: nesting ratio
  - Quantization error $D_{sc}=q^2/12$
  - D_{cc} is inversely proportional to $d_{min}=Nq$
- For a fixed N, optimal q searched to minimize $D=D_{sc}+D_{cc}$

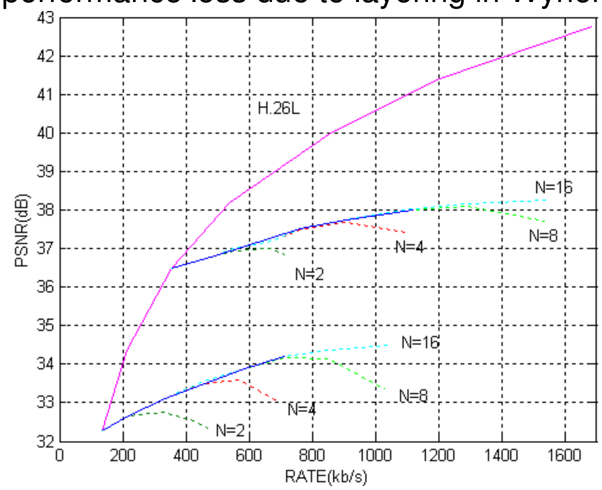
Multilevel Slepian-Wolf Coding

- LDPC code based bit plane coding for SWC
  - Each bit plane coded into one layer – layered bitstream
  - Exploits the correlation between the quantized version of the source and the side information



Successive Refinement

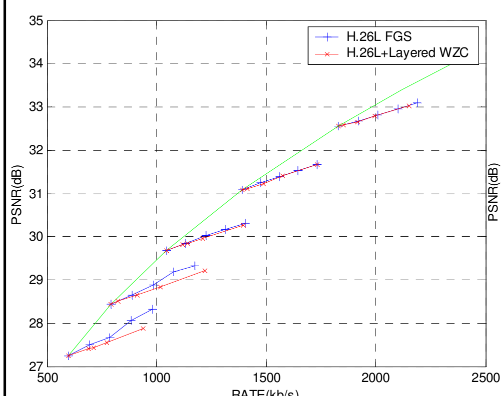
- Assume ideal Slepian-Wolf coding
  - No performance loss due to layering in Wyner-Ziv coding



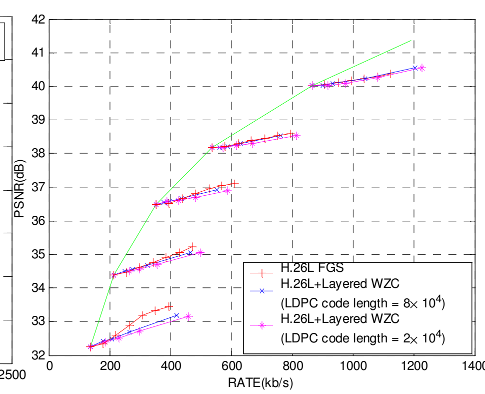
CIF Foreman

Layered Wyner-Ziv Video Coding

- Results (slightly worse than H.26L-FGS at high rate)



CIF Football



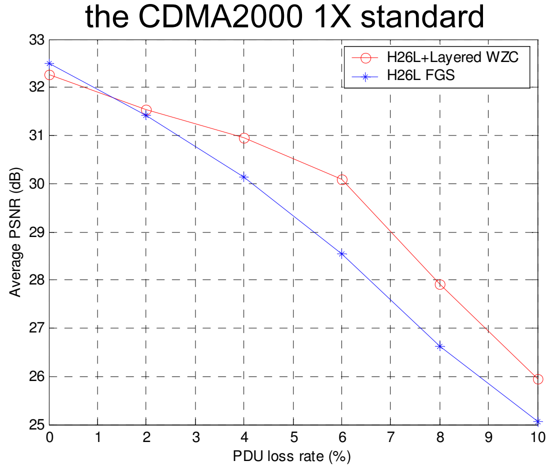
CIF Foreman

WZC of video for Error Resilience

- Similar to Fine Granularity Scalable (FGS) coding
  - Having an embedded enhancement layer with good R-D performance
- Key advantage: error robustness over H.26L FGS
  - FGS coding: Encode the difference between the original video and the base layer reconstruction as the enhancement layer
  - Wyner-Ziv video coding: Use the H.26L coded version as the side information, and apply WZC to the original video

Advantage over H.26L-FGS Coding

- Simulation with Qualcomm wireless channel simulator
  - Add packet errors to streams of RTP packets conforming to the CDMA2000 1X standard



"Football" sequence, IPPP

Both the base layer and the enhancement layers are packetized and protected with rate 0.80 RS code before being transmitted through the simulator

Performance averaged over 200 transmissions

Advantage over H.26L-FGS Coding

- Error resilience against errors in the base layer

H.26L-FGS H.26L+WZC

CIF Foreman (5% lost macroblocks in the base layer)

WZC of Video for Error Resilience

- Example: The 10th decoded frames of Football
  - Protected with rate 0.80 RS-based FEC, and transmitted over a simulated CDMA2000 1X channel with 6% PDU loss rate

FGS coding
PSNR = 23.9 dB

Layered Wyner-Ziv video
coding PSNR = 28.8 dB

Tutorial Outline

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- Layered Wyner-Ziv video coding
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III. DVC roadmap

- Scalable Slepian-Wolf coding
- Correlation modeling and universal Slepian-Wolf coding
- Practical low-complexity and high-efficiency DVC

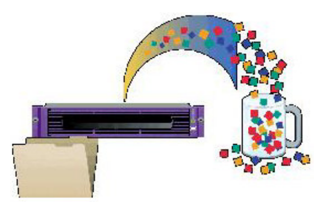
Distributed joint source-channel coding

- The Slepian-Wolf coded syndromes are very sensitive to channel errors
- Efficient channel codes are needed to protect the syndromes
- Approach one (PCS'04)
  - Combined Wyner-Ziv coding and channel coding
    - Wyner-Ziv coding and fountain codes for receiver-driver layered multicast (RLM)
- Approach two (DCC'05 & ICIP'05)
  - Parity-based distributed JSCC (one channel code for both Slepian-Wolf coding and error protection)
    - Distributed JSCC of video using raptor codes (IRA precode + LT code)

From RS to Raptor Codes

- Reed-Solomon codes (1960)
  - Capacity achieving
  - Quadratic encoding/decoding complexity
- Tornado codes (Luby et al.'97)
  - Slightly below the capacity
  - Linear encoding/decoding complexity
- Rateless digital fountain codes
  - Developed from Tornado codes
    - LT codes (Luby'98)
    - Raptor codes (Shokrollahi'01)
      - A linear precode + LT code

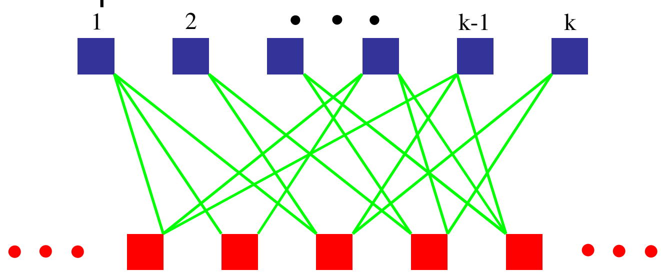
Digital Fountain



- Data is like water (Luby):
  - We do not care what drops we get
  - We do not care if some spills
  - We just want enough to get through the pipe

LT Codes

- The first realization of a digital fountain
- Example



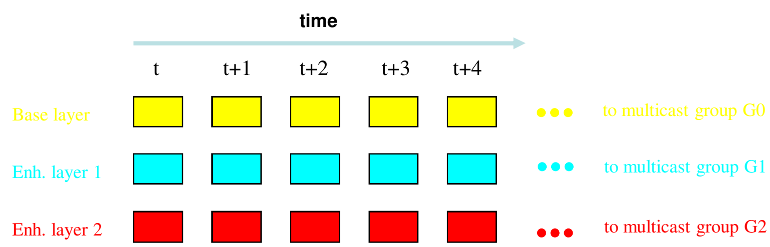
- Any $k(1+\varepsilon)$ received symbols will guarantee symbol recovery
- Rateless codes – potentially unlimited number of symbols can be generated on the fly

Fountain Codes for Multicast

- Packets are generated on the fly at the server (to form a digital fountain)
- Receivers can join the multicast group to "drink" from it just long enough to receive enough packets
- Linear encoding/decoding complexity
- Near-capacity performance

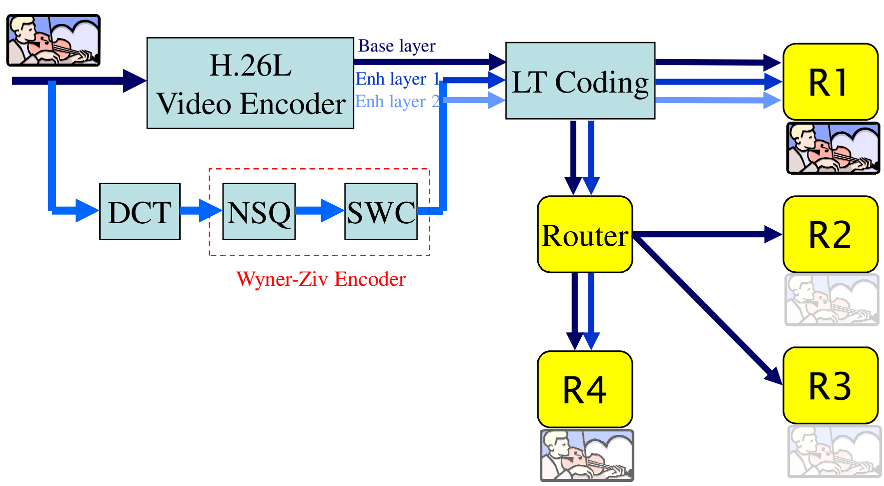
Receiver-driven Layered Multicast (RLM)

- Layered source coding
- Each layer sent to different multicast group



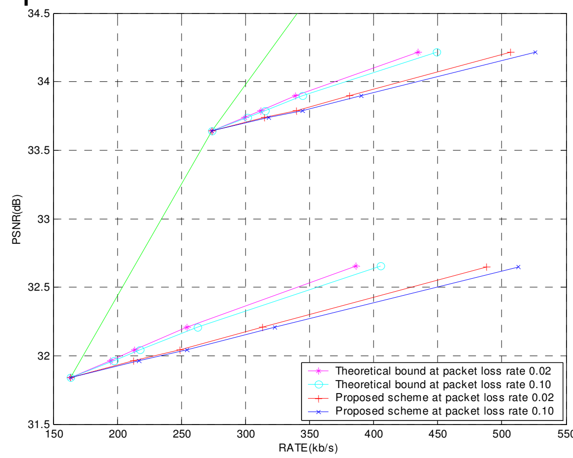
- Receivers subscribe to as many layers as possible (within their resource constraints)

Wyner-Ziv Video Coding and Fountain Codes for RLM



Experiment Results

- Coding performance with perfect base layer and the different packet loss rates for the enhancement layers



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Only 0.07 b/s away from the theoretical limit

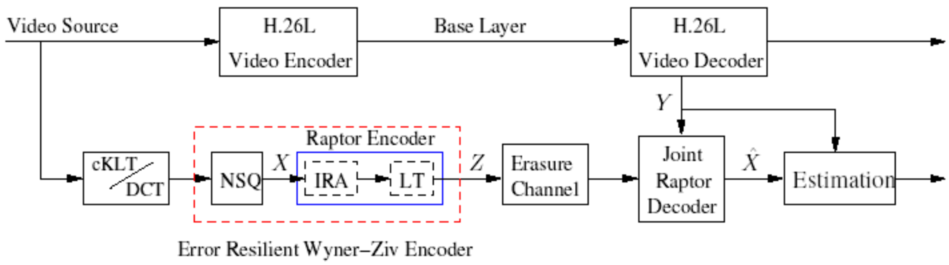
Experiment Results (PCS'04)

First multicast group (273 Kb/s)
PSNR = 33.6dB

Second multicast group (431 Kb/s)
PSNR = 34.2 dB

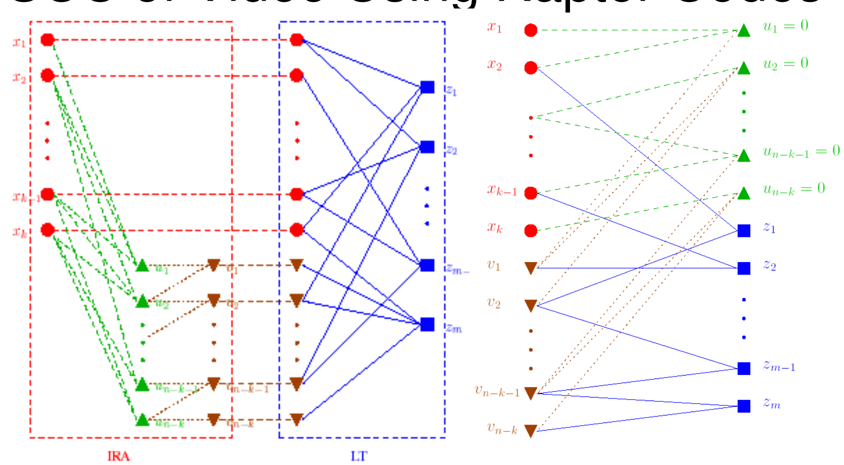
JSCC of Video Using Raptor Codes

- Distributed JSCC for video transmission over packet erasure channels



- A *single* raptor code for both SWC and erasure protection (IRA precode and LT code)
- Raptor codes – the best approximation to a digital fountain

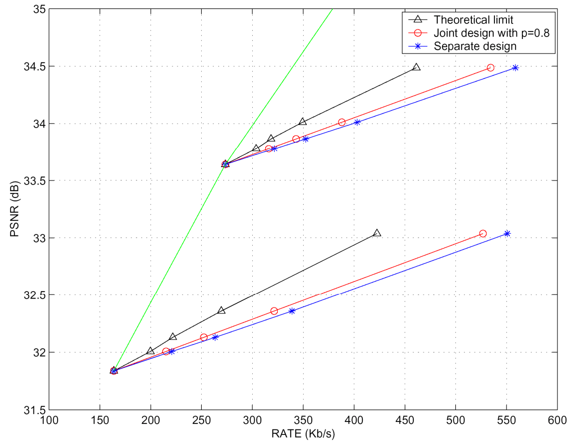
JSCC of Video Using Raptor Codes



- IRA codes: Good candidate for distributed JSCC
  - Parity part for the real channel; systematic part for the correlation channel
  - A bias towards selecting IRA parity symbols versus systematic symbols in forming the bipartite graph of the LT code

DJSCC Simulations

- Coding performance with perfect base layer and packet loss rate for the enhancement layer is 0.1



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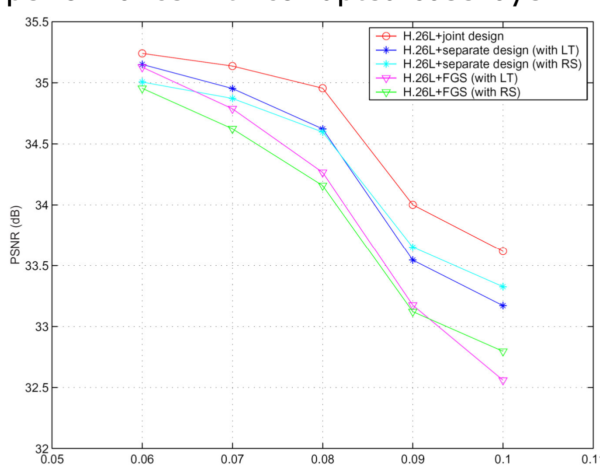
7-9% less number of packets are required with the joint Raptor design

DJSCC Simulations

- Coding performance with corrupted base layer



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- All five schemes are designed assuming channel packet loss ratio 0.1
- Performance averaged over all 20 frames and 100 transmissions

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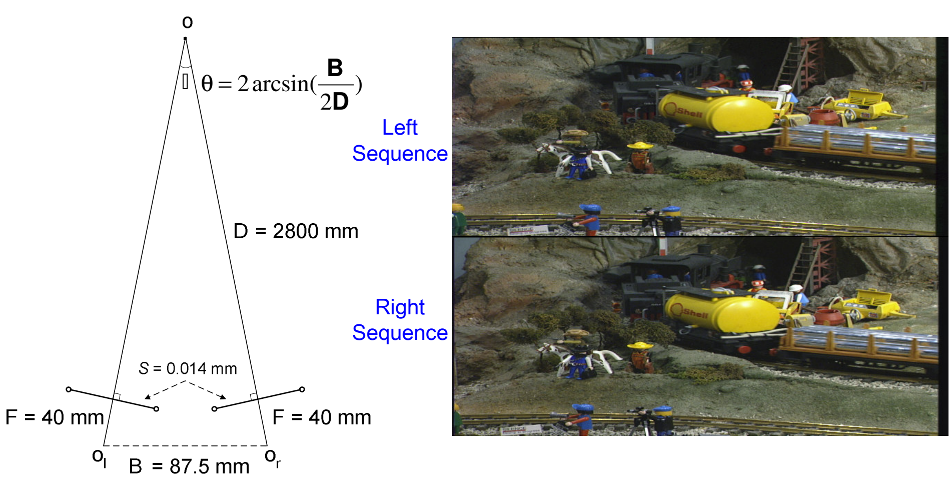
Multiterminal Video Coding

- Stereo camera setup (in a video sensor network)

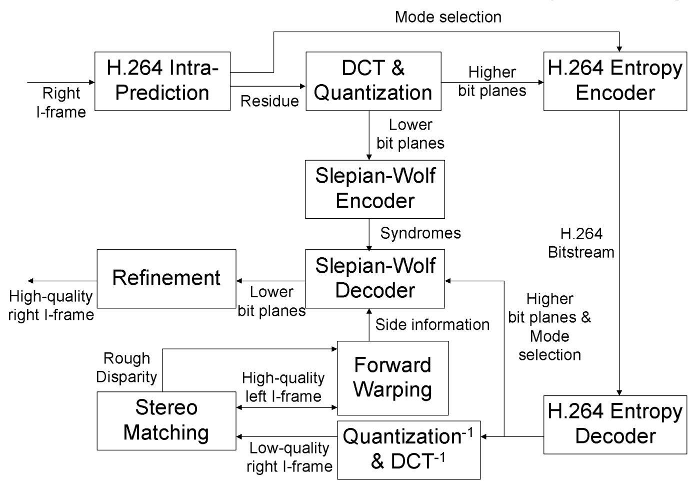


MT Video Coding

- Overview of proposed scheme (along the line of Slepian-Wolf coded quantization)
  - The left sequence coded with standard H.264 (IPPP…P)
  - Compression of the first I-frame of the right sequence
    - Low-quality H.264 intra coding + Wyner-Ziv enhancement
  - Compression of the P-frames of the right sequence
    - BP based stereo matching -> disparity map at joint decoder
    - Motion fusion -> estimate of right motion field
    - Generation of side information
      - For motion vectors of the right sequence
      - For H.264 MC residual frames of the right sequence
    - Slepian-Wolf coding of motion vectors of the right sequence
    - Wyner-Ziv coding of MC residual frames

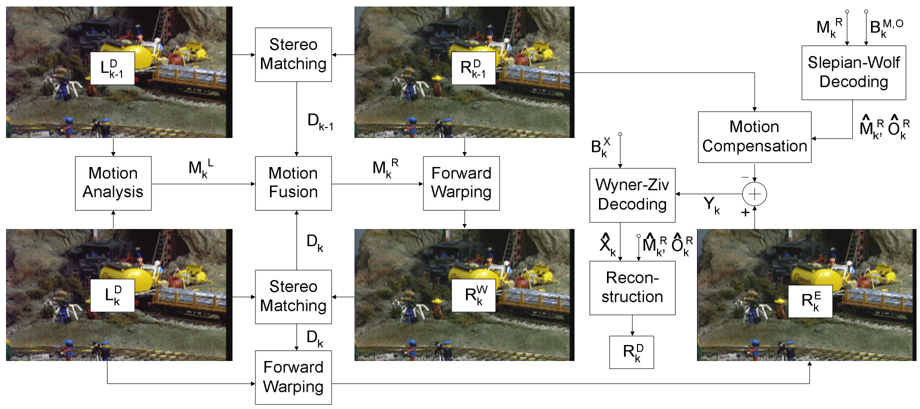
MT Video Coding

- Proposed scheme (for I-frame of right sequence)



MT Video Coding

- Proposed scheme (for P-frames of right sequence)



$$X_k = R_k - R_k^M; \qquad Y_k = R_k^E - R_k^M$$

MT Video Coding

- Stereo matching (a large body of works from computer vision)
  - Minimizes the image disimilairity energy
  - Quantitative evaluations of different stereo matching algorithms
    - http://cat.middlebury.edu/stereo
    - BP based stereo matching is among the best
  - Our pick: the algorithm of Sun et al. ’03 at Microsoft
    - Three coupled Markov random fields (a smooth disparity field, a spatial line process, and a binary occlusion process)

MT Video Coding

- Disparity map from a simplified stereo matching algorithm

720x288

720x288

MT Video Coding

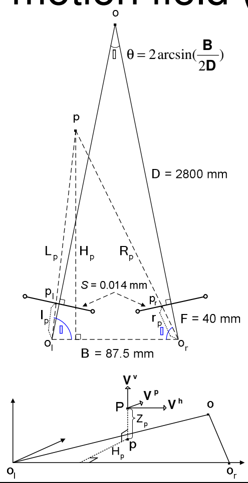
- Motion field (in the left sequence) from motion analysis using a stereo-matching-like algorithm

720x288

720x288

MT Video Coding

- Motion fusion of the disparity map and the left motion field (to predict the 2nd right frame)



Disparity Map $p_l \leftrightarrow p_r$ → (α, β) → Depth Map H_p → Motion Fusion → Right motion field M^R

Pixel size S, Focal length F, Convergence distance D, Base length B, Left motion field M^L

$$\alpha = \frac{\pi-\theta}{2} + \arctan\frac{S \cdot p_l}{F}$$

$$\beta = \frac{\pi-\theta}{2} - \arctan\frac{S \cdot p_r}{F}$$

$$H_p = \frac{B}{\frac{1}{\tan(\alpha)} + \frac{1}{\tan(\beta)}}$$

$$\frac{v_r^h}{v_l^h} = \frac{r_p L_p}{l_p R_p} = \frac{r_p \sin(\beta)}{l_p \sin(\alpha)} = \frac{\sin(\alpha + \frac{\theta}{2})\sin(\beta)}{\sin(\beta + \frac{\theta}{2})\sin(\alpha)}$$

$$\frac{v_r^v}{v_l^v} = \frac{\sin(\alpha + \frac{\theta}{2})\sin(\beta)}{\sin(\beta + \frac{\theta}{2})\sin(\alpha)}$$

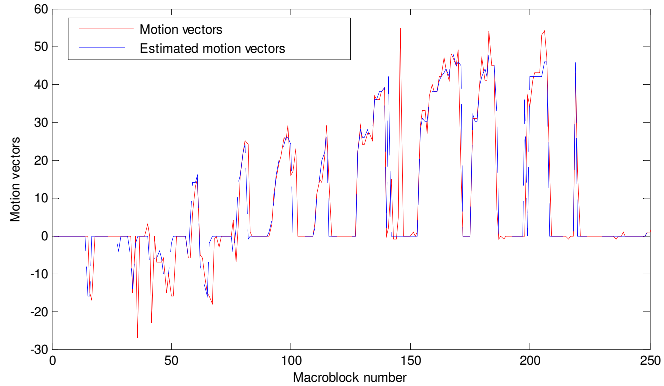
MT Video Coding

- H.264 experiment parameters

	Low rate regime	High rate regime
Total # of frames	20	20
QP I frame	35	Q_h=22, Q_l=34
QP P frames	33	20
Motion search	16x16,8x16,16x8	16x16,8x16,16x8
MV precision	quarter-pel	quarter-pel
Bit rate (both)	860.6 kb/s	6501.0 kb/s
Average PSNR	31.14 dB	40.59 dB

MT Video Coding

- Experimental results
  - Motion vectors of the right sequence and our generated side information



  - Most challenging part: Correlation modeling

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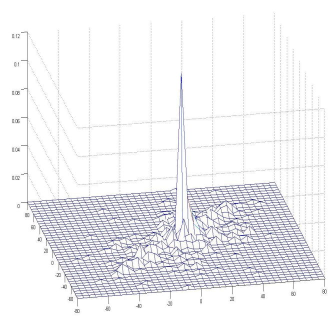
MT Video Coding

- Correlation modeling (motion vectors)
  - Motion vector difference (MVD)
    - Explores memory in motion vectors: MVD = MV - MVp
    - Used by H.264 for motion vector compression
  - Collect joint statistics of MVDs and estimated MVDs for all 19 P-frames: a generic model
  - Multilevel Slepian-Wolf coding of MVDs for each frame
    - Generate conditional probabilities based on the generic model
    - Top bit-planes: LDPC code based Slepian-Wolf coding
    - Bottom bit-planes: entropy coding



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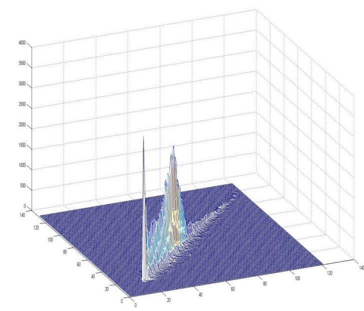
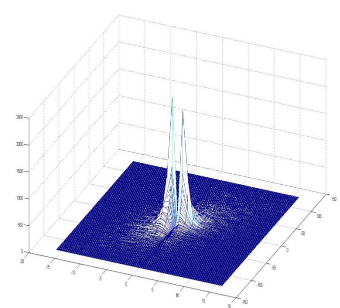
MT Video Coding

- Correlation modeling (I-frame residual coefficients)
  - 4x4 DCT coefficients are compressed separately
  - Collect joint statistics of each 4x4 DCT coefficients and estimated DCT coefficients from all 20 frames: 16 generic models
  - Slepian-Wolf coding of *k* refinement bit planes for the j^{th} position
    - Generate conditional probabilities based on the j^{th} generic model and the decoded higher bit planes
    - Low-frequency coefficients: LDPC code based Slepian-Wolf coding
    - High-frequency coefficients: entropy coding
  - Example of the generic model for the DC coefficients



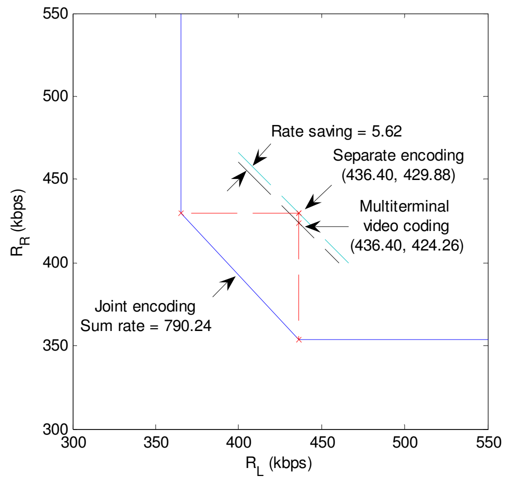
MT Video Coding

- Correlation modeling (P-frame residual coefficients)
  - H.264 entropy coding of residual coefficients: cbp, run, level, …
    - Only quantization levels are Slepian-Wolf coded
  - Collect joint statistics of quantization levels of residual coefficients and estimated residual coefficients from all 19 P-frames: a generic model
  - Multilevel Slepian-Wolf coding of quantization levels
    - Generate conditional probabilities based on the generic model
    - Top bit-planes: LDPC code based Slepian-Wolf coding
    - Bottom bit-planes: entropy coding
  - Example of the generic model for the quantization levels



MT Video Coding

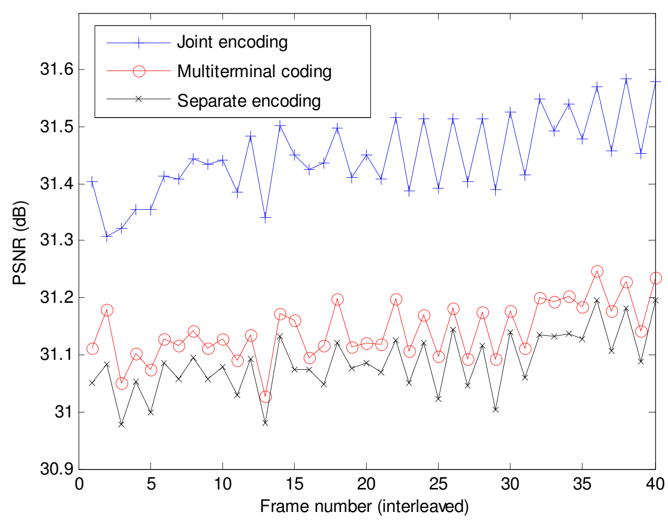
- Experimental results (average PSNR=31.14 dB)



Rate savings from Slepian-Wolf coding of motion vectors

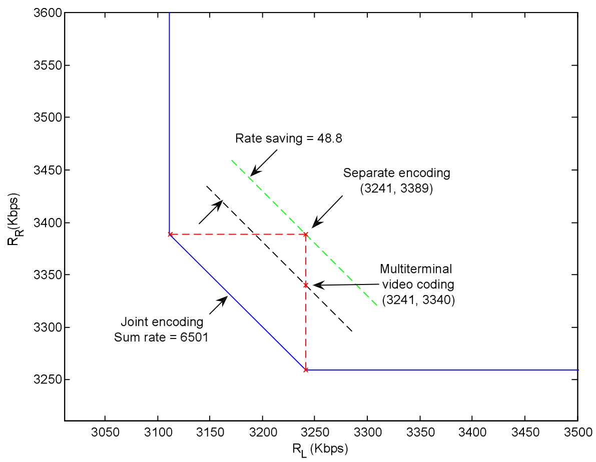
MT Video Coding

- Experimental results (at sum-rate of 860.6 kb/s)



MT Video Coding

- Experimental results (average PSNR=40.59 dB)



Rate savings from successive coding of I-frames and Wyner-Ziv coding of MC residual frames

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DVC Roadmap

- DVC research still in its infancy
- Lots of opportunities for new research directions
  - DVC for receiver cooperation is a new and exciting application area
  - Combined DVC and network coding also holds promise
- Immediate research issues
  - Correlation modeling
  - Design of short, but high-performing channel codes for Slepian-Wolf compression
  - Practical and high-performance DVC systems
- Bigger challenges
  - Scalable Slepian-Wolf coding
  - Universal Slepian-Wolf coding

DVC Roadmap

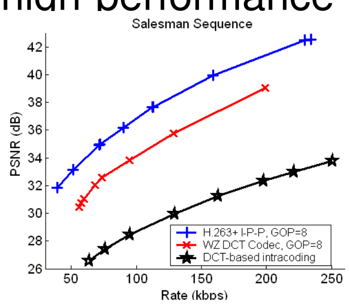
- Correlation modeling for DVC
  - Based on training sequences
    - Layered Wyner-Ziv coding (Xiong'04)
    - PRISM (Ramchandran'02)
    - Multiterminal video coding (Xiong'07)
      - Use a training set (much like with vector quantization)
  - MC at the decoder
    - PRISM (Ramchandran'02)
  - Prediction and estimation
    - Universal prediction of side information (Delp'06)
    - DISCOVER team'06
  - Side information critical in Wyner-Ziv video coding

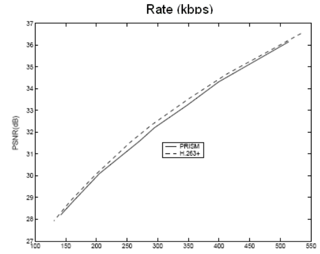
DVC Roadmap

- Design of short (but good) channel codes for Slepian-Wolf compression
  - To reduce delay/latency in DVC
- Redundancy of Slepian-Wolf coding
  - $K(\epsilon)/\sqrt{n}$ with ϵ being the error probability and n the code length
  - Very long code length for efficient Slepian-Wolf coding
  - Based on training sequences
- Recent work on good short codes
  - Quasi-cyclic LDPC codes (Fossorier'04)
  - Protograph LDPC Codes (NASA/Divsalar'06)
  - Provably good LDPC codes (Qualcomm/Richardson)

DVC Roadmap

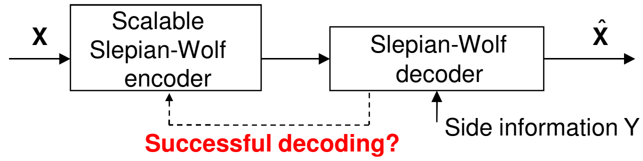
- Practical low-complexity, high-performance DVC
  - DCT-domain Wyner-Ziv video coding (Girod)
    - Relatively low complexity
    - Easy to reproduce
    - Large performance gap to H.263+
  - PRISM (Ramchandran)
    - High decoding complexity
    - Relatively high performance
    - Not easy to reproduce





DVC Roadmap

- Scalable Slepian-Wolf Coding
  - When the source correlation is perfectly known, Slepian-Wolf coding is in general a channel coding problem
  - Bit-plane based layered coding
- When the source correlation is not known in DVC
  - Decoder feedback is needed



DVC Roadmap

- Rate-adaptive Slepian-Wolf coding
  - Serially concatenated-accumulate codes (Yedidia'04)
  - Rate-compatible LDPC codes (Fekri'05)
  - Rate-adaptive LDPC accumulate codes (Girod'05)
  - Sum LDPC accumulate codes (Girod'05)
  - Rateless Slepian-Wolf coding (Yu'05, Jiang'07)
  - Fountain codes for Slepian-Wolf coding (Shokrollahi'06)
- Raptor codes for scalable Slepian-Wolf coding
  - All bits are created equally in conventional Raptor codes
  - Scalable source coding leads to sequential dependency
    - First bit more important than second, etc
    - Bias towards earlier parity bits when making random connections to source symbols (similar to Raptor codes with UEP)

DVC Roadmap

- Universal Slepian-Wolf coding
  - The most challenging problem when joint statistics not known a priori in DVC
    - Csiszar's 1982 paper showed existence of universal decoder
- Recent work (Baron'05, Yang'06, Yang'07)
  - Do not treat is as a channel coding problem
  - Borrow ideas from traditional lossless compression
  - Use feedback and threshold decoding
    - The feedback rate goes to zero asymptotically
    - But threshold decoding is currently too difficult and complex

Acknowledgment

- I'd like to gratefully acknowledge the following staff members in my lab, for without their dedication to research, none of the works presented here would be possible
  - Sam Cheng
  - Tim Lan
  - Zhixin Liu
  - Angelos Liveris
  - Vladimir Stankovic
  - Qian Xu
  - Yang Yang

References

- See http://www.discoverdvc.org for an extensive list