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Distributed Source Coding for Video and Image Applications
From Theory To Practice

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Multi-view Video Compression

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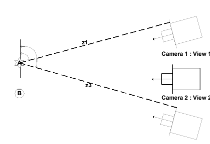
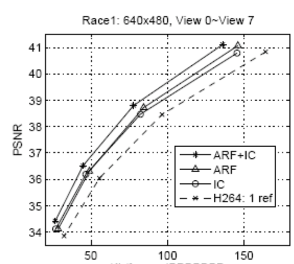
- Funding: Thomson Corporate Research
- Students: Jae Hoon Kim, PoLin Lai
- Improvements to inter-view coding in MVC
  - Heterogeneous camera settings
  - Illumination compensation (IC)
  - Adaptive reference filtering (ARF)





•Publications ('07-'08)

–J. H. Kim, P. Lai, J. Lopez, A. Ortega, Y. Su, P. Yin, and C. Gomila, "New Coding Tools for Illumination and Focus Mismatch Compensation in Multiview Video Coding," in IEEE Trans. Circuits and Systems for Video Technology, Vol. 17, No. 11, pp. 1519-1535, Nov. 2007.

–P. Lai, A. Ortega, P. Pandit, P. Yin, and C. Gomila, "Focus Mismatches in Multiview Systems and Efficient Adaptive Reference Filtering for Multiview Video Coding", in Proc. SPIE 2008 Visual Communications and Image Processing (VCIP), Jan 2008.

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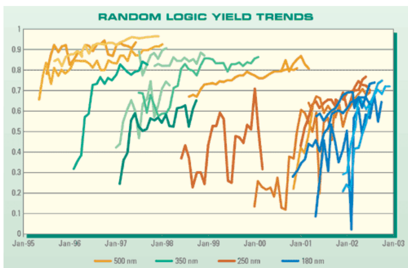
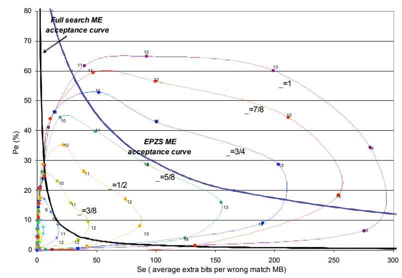
Error tolerant multimedia compression

- **Funding:** NSF
- **PIs**: Melvin Breuer, Keith Chugg, Sandeep Gupta, Antonio Ortega
- **Students**: Hye-Yeon Cheong, In-Suk Chong, Zhaoliang Pan, Shideh Shahid, On Wa Yeung



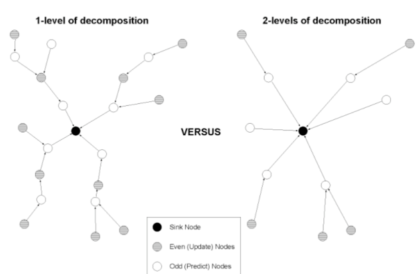
R.C. Leachman and C.N. Berglund, "Systematic Mechanisms-Limited Yield Assessment Survey," Competitive Semiconductor Manufacturing Program, UC Berkeley, 2003



Acceptable fault: PSNR impact, error rate, error significance
Large percentage of SSF are acceptable (e.g., 99% lead to less than 0.01dB degradation).

Efficient Sensor Web Communication Strategies Based on Jointly Optimized Distributed Wavelet Transform and Routing

- **USC:** A. Ortega (PI), B. Krishnamachari, S. Lee, S.W. Lee, S. Pattem, G. Shen, A. Tu
- **NASA JPL:** M. Cheng, S. Dolinar, A. Kiely, M. Klimesh, H. Xie
- **Funding:** NASA grant AIST-05-0081
- Interactions between routing, transforms and quantization
- Implementation using Motes



- **Publications ('07-'08):**
  - G. Shen and A. Ortega, "Optimized Distributed 2D Transforms for Irregularly Sampled Sensor Network Grids Using Wavelet Lifting," accepted for publication in *Proc. of 2008 IEEE Intl. Conf. on Acoustics, Speech and Signal Processing, ICASSP '08*, 2008
  - G. Shen and A. Ortega, "Joint Routing and 2D Transform Optimization for Irregular Sensor Network Grids Using Wavelet Lifting," accepted for publication in *IPSN '08: Proc. of the Fifth Intl. Conf. on Information Processing in Sensor Networks*, 2008

MADCAT – Maltraffic Analysis and Detection in Challenging and Aggregate Traffic

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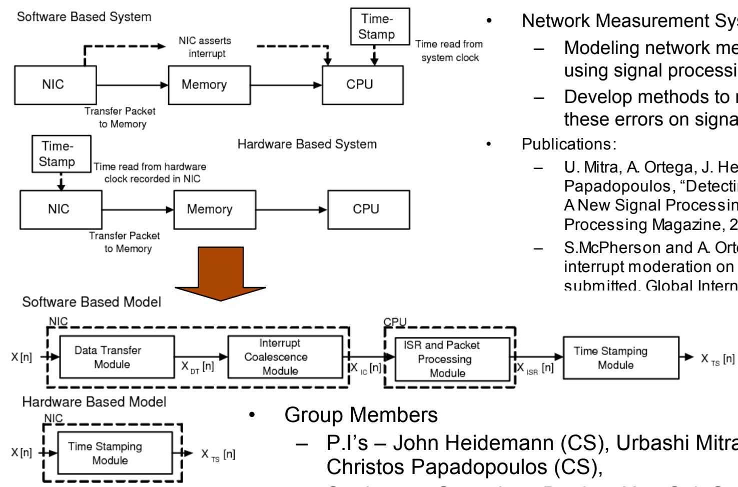

- Network Measurement System Modeling
  - Modeling network measurement systems using signal processing modules
  - Develop methods to mitigate the effect of these errors on signal analysis
- Publications:
  - U. Mitra, A. Ortega, J. Heidemann and C. Papadopoulos, "Detecting and Identifying Malware: A New Signal Processing Goal", IEEE Signal Processing Magazine, 2006.
  - S.McPherson and A. Ortega, "Modeling the effects of interrupt moderation on network measurements", submitted, Global Internet Symposium, 2008

- Group Members
  - P.I's – John Heidemann (CS), Urbashi Mitra, Antonio Ortega, Christos Papadopoulos (CS),
  - Students – Genevieve Bartlett, Xue Cai, Sean McPherson, Gautam Thatte
- Website – http://isi.usc.edu/ant

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Support - MADCAT is supported by the NSF's NeTS program, grant number CNS-0626696

Signal Processing for Oilfield Data Mining

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Students: Kun-Han Lee and Yen-Ting Lin

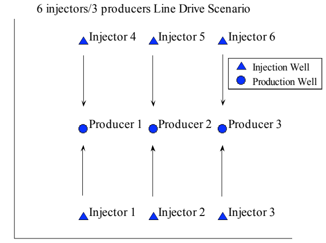
Collaborators: I. Ershaghi (PTE)

Funding: Chevron Corp.

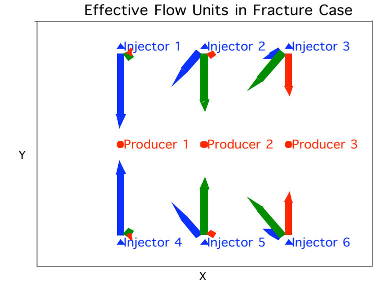
Publications ('07-'08):

•K.-H Lee, A. Ortega, I. Ershaghi, "A Method for Characterization of Flow Units Between Injection-Production Wells Using Performance Data", 2008 SPE Western Regional and Pacific Section AAPG Joint Meeting, March 2008.

6 injectors/3 producers Line Drive Scenario



Effective Flow Units in Fracture Case



- Goal:
  - Inference of oilfield geological characteristics based on water injection/oil production data.
- Tools:
  - Wavelet-based methods
- Analysis and simulation; planned field testing

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Genome Copy Number Alteration Detection

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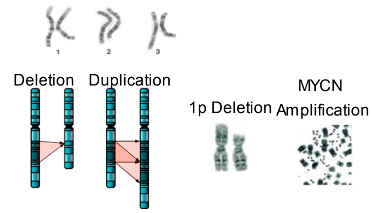
Genome copy number alterations (CNA) linked with cancer and other conditions

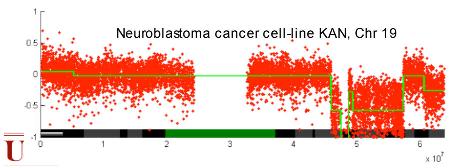
Highly noisy data, very large number of probes.



Signal processing problem:

- Find optimal piecewise constant sparse approximation
- Matching pursuits/basis pursuits inefficient due to high coherence dictionary
- Sparse Bayesian Learning can handle coherent dictionaries and can operate in linear time.

- Results comparable to state of art (e.g., segmentation based techniques) with 10x speed-up



R. Pique-Regi, J. Monso-Varona, A. Ortega, R. Seeger, T. Triche and S. Asgharzadeh, “Sparse representation and Bayesian detection of genome copy number alterations from array data", Bioinformatics, Jan. 2008.

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Acknowledgements

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- Collaborators at USC:
  - Dr Ngai-Man Cheung
  - Dr Huisheng Wang (now at Google)
  - Caimu Tang
  - Ivy Tseng
- Outside Collaborators:
  - Sam Dolinar (NASA-JPL)
  - Aaron Kiely (NASA-JPL)
  - Kannan Ramchandran (UCB)
- Funding:
  - NASA-JPL
  - NSF

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Mystery Graph?

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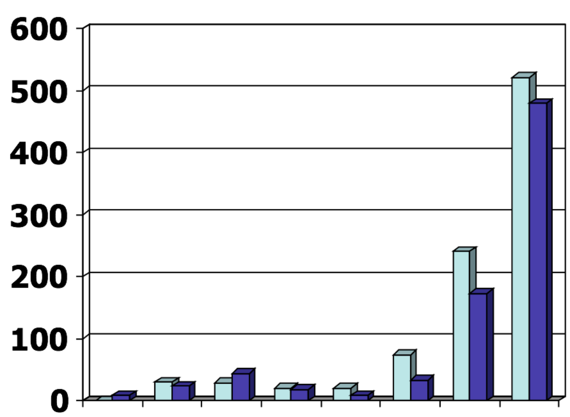

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Distributed Source Coding (DSC)

- Information-theoretic results from 1970s
  - Lossless: [Slepian, Wolf; 1973]
  - Lossy: [Wyner, Ziv; 1976]
- Practical application until recently [Pradhan, Ramchandran; DCC 1999]
  - Dense sensor network
  - Practical encoding/decoding algorithm
- Application to video compression [Puri, Ramchandran; Allerton 2002], [Aaron, Zhang, Girod; Asilomar 2002]
  - Low complexity encoding
  - Distributed video coding, Wyner-Ziv video
- Other applications to video/image compression
  - Error resilience
  - Low complexity scalable video encoding
  - Hyperspectral imagery compression
  - Multiview video coding

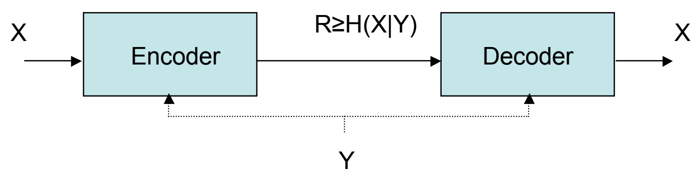
Outline

- Introduction
  - Distributed Source Coding
  - Example application scenarios
  - Practical DSC techniques
  - Key Problems
- Applications/Case studies
  - Scalable video coding
  - Hyperspectral image coding
  - Flexible video decoding

Distributed Source Coding: Fig. 1

Lossless compression of random variable X
- Intra coding: R ≥ H(X)

(i) Predictive (e.g. DPCM):

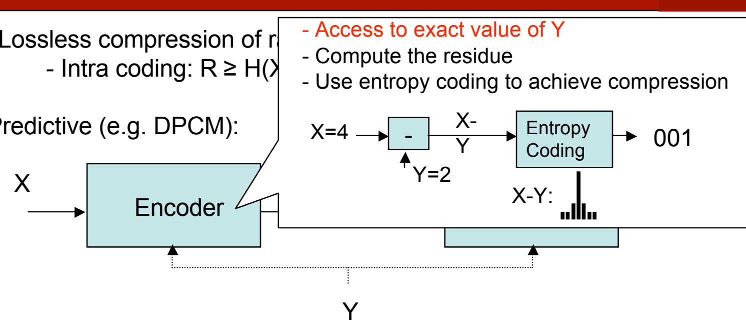


(ii) DSC:

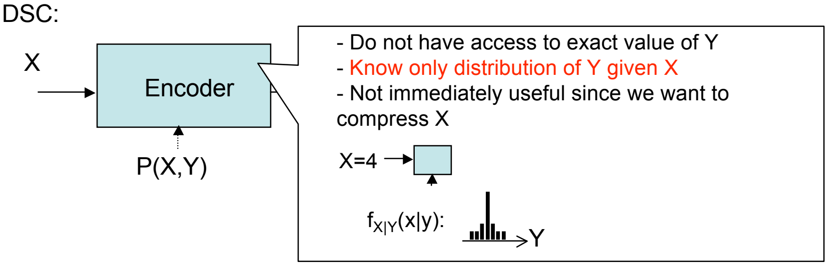
Distributed Source Coding: Fig. 1

Lossless compression of r
- Intra coding: R ≥ H(X

(i) Predictive (e.g. DPCM):



(ii) DSC:



Distributed Source Coding: Fig. 1

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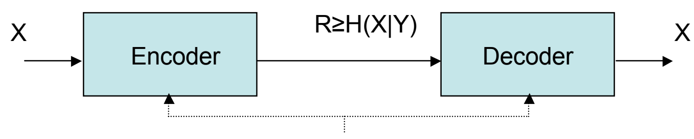
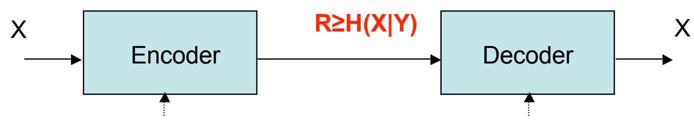
Lossless compression of random variable X
- Intra coding: $R \geq H(X)$

(i) Predictive (e.g. DPCM):



[Slepian, Wolf; 1973]

(ii) DSC:



Efficient encoding possible even when encoder does not have precise knowledge of Y

How can we encode X in this case?

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Example Slepian-Wolf Coding

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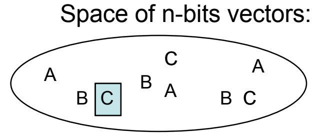
- **X**={X}, **Y**={Y}, to compress a n-bits binary vector **X**
- Correlation: binary symmetric channel with crossover probability p

Encoder:

- Partition input space into cosets:
- Send coset index:

X mod m = coset index

Space of n-bits vectors:

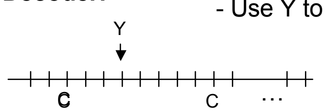


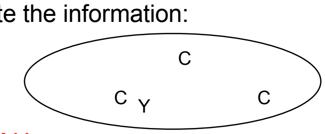
2^{n-k} cosets

$\mathbf{X}\,\mathbf{H}^T = \mathbf{S}$

Decoder:

- Use Y to disambiguate the information:





- Compression performance: (n-k)/n

- Number of cosets (min. distance between members of coset) depends on correlation

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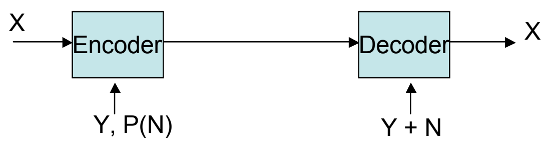
Application scenarios - 1

Robustness to channel losses:

- Achieving deterministic decoding with non-deterministic input to the decoder
- Have to estimate noise power at the encoder

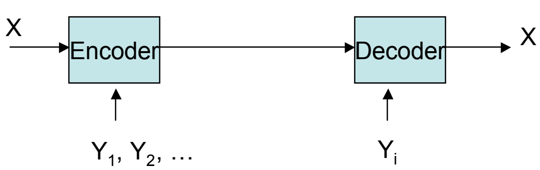


[Sehgal, Jagmohan, Ahuja; IEEE Trans. Multimedia 04], [Majumdar, Wang, Ramchandran, Garudadri; PCS 04], [Rane, Girod; VCIP 06], etc

Application Scenarios - 2

Flexible playback:

- Exploit correlation between input and multiple side information
- Decoder can use Y_1 OR Y_2 OR … etc



[Cheung, Wang, Ortega; VCIP 06][Cheung, Ortega, MMSP'07, PCS'07, VCIP'08

Application Scenarios - 3

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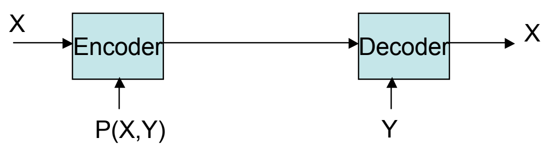
Low complexity encoding

- If finding Y to predict X is complex, but..
- P(X,Y) can be estimated in low complexity



[Puri, Ramchandran, Allerton 02]
[Aaron, Zhang, Girod, Asilomar 02], etc

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Practical Lossy DSC: Components

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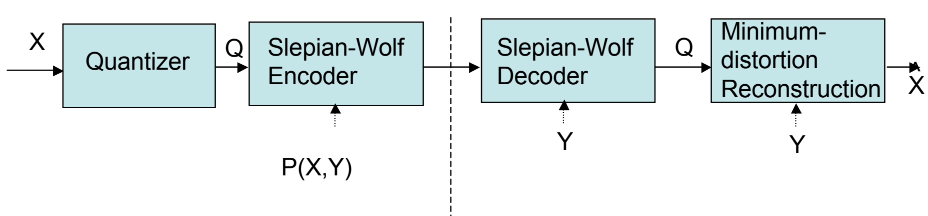

- Lossy quantization
  - In many cases following a transform
- Lossless compression of quantization index Q using SW encoder
  - Convert to binary data (e.g., bitplanes):
    - Transmit LSB
    - Select codes use syndrome coding
- At decoder, side information Y is used in:
  - Slepian-Wolf decoding
  - Reconstruct X in the quantization bin specified by Q: use as reconstruction the expected value given Y, conditioned on bin Q

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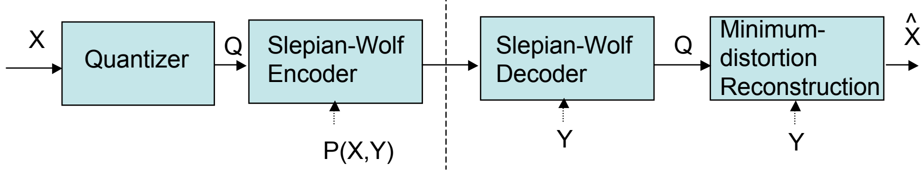
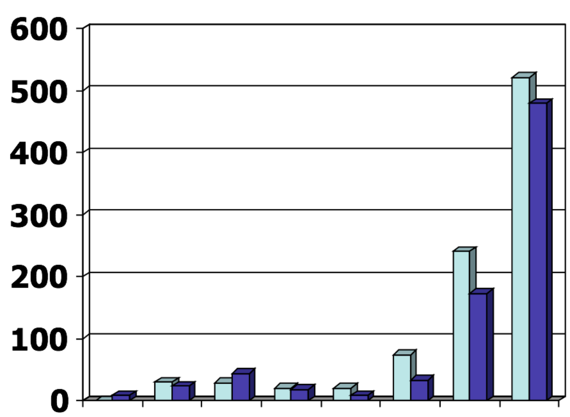
Practical Lossy DSC: Key Problems



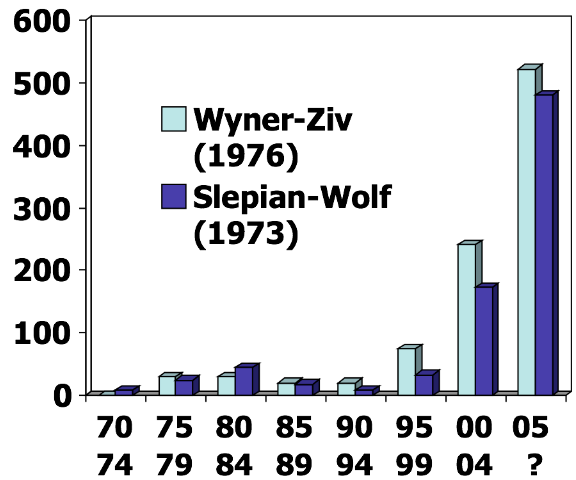
- **Defining the application:**
  - Loss in RD performance due to DSC (even in theory)
  - What is the other metric that we want to optimize? (complexity, memory, speed)
- **Formulating correlation model estimation problem:**
  - Lower modeling accuracy leads to coding penalty
  - Better modeling may reduce benefits in terms other metric (e.g., complexity)
- **For a given design, how to optimize RD performance:**
  - When to use DSC and when not to (e.g., use Intra coding instead)?
  - Optimize trade-off in terms of RD and/or Complexity, etc
- **This Talk**:
  - Case studies to illustrate the benefits of focusing on these issues.

Mystery Graph?



Total citations per 5 year period

Source: Google Scholar



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  - Flexible video decoding

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DSC Application to Scalable Video Coding

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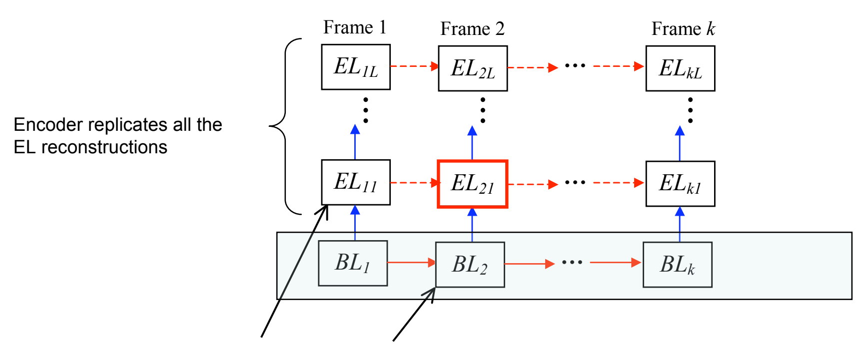
Optimal Scalable Video Coding with Multiple Motion-Compensated Prediction (MCP) Loops

Multiple MCP loops approach
[Rose, Regunathan; IEEE Trans. IP 2001]



Use both BL and EL for prediction: good coding efficiency

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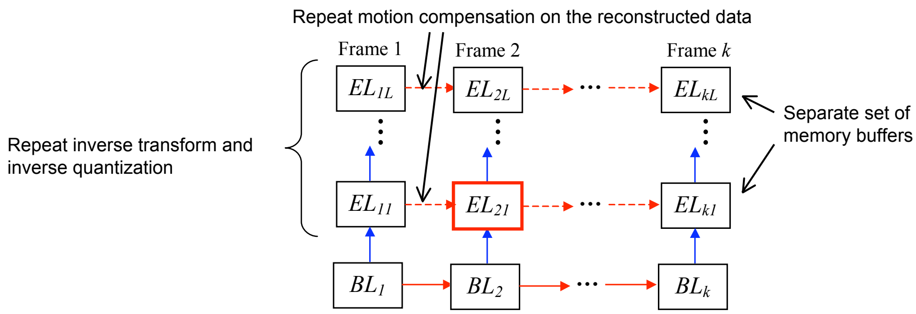
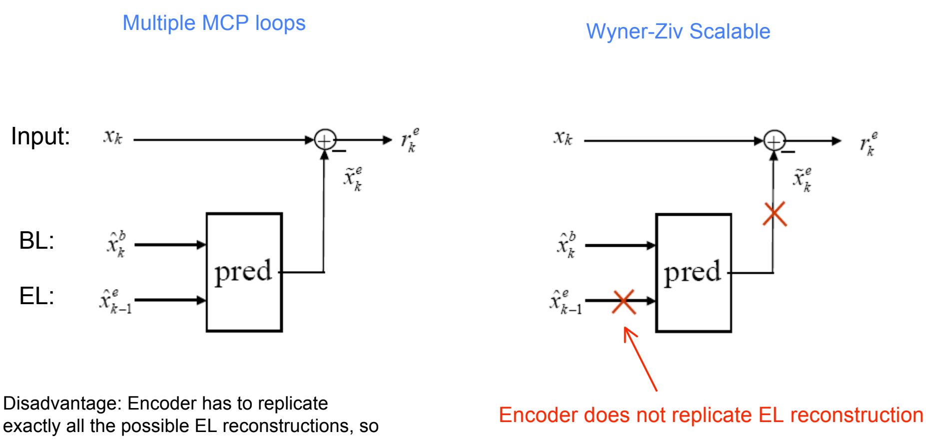
Multiple MCP Loops Approach: Non-trivial Complexity

In multiple loops approach, the complexity of replicating all the EL reconstructions could be non-trivial in multiple layers coding



- **Low complexity alternative: Temporal prediction only in base layer (FGS)**
- **Our contribution: DSC counter-part to the multiple loops approach to achieve low complexity encoding (WZS)**

WZS: Encoder does not replicate EL reconstruction



Disadvantage: Encoder has to replicate exactly all the possible EL reconstructions, so that the prediction residue can be computed

Cast scalable coding as a Wyner-Ziv problem

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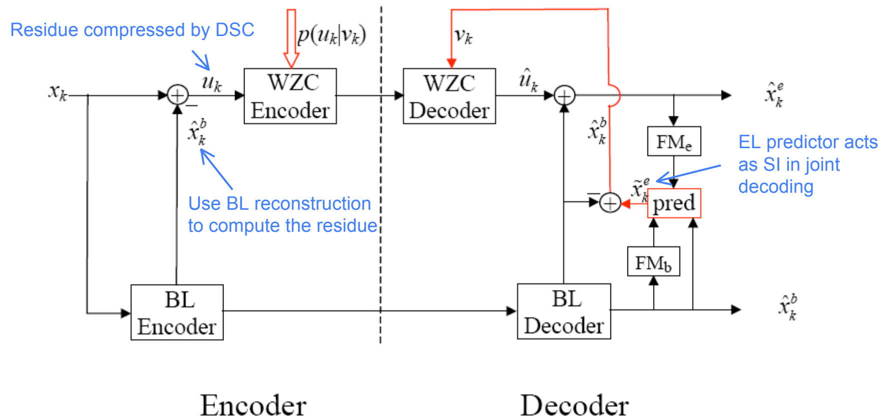

To estimate the difference between input and base layer (u_k) we use the difference between best predictor and base layer (v_k)

How to estimate $p(u_k|v_k)$?

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Wyner-Ziv Scalable Video Coding (WZS) – Overview

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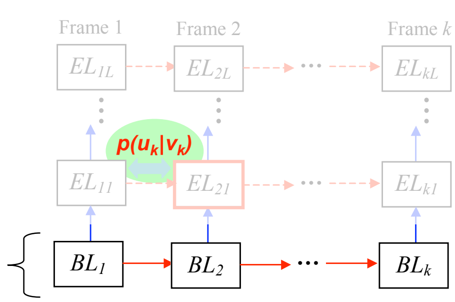
WZ scalable coding: Encoder does not replicate EL reconstruction
- EL predictor available only at decoder
- Side Information: EL predictor



Encoder replicates only BL reconstruction

Key point: DSC requires only the correlation information instead of the exact reconstructed data in encoding

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Correlation Estimation at Encoder

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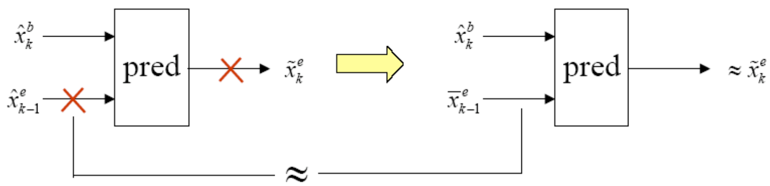
- Solution
  - Approximate optimal predictor
  - Using an approximation of EL reconstruction

$$\overline{x}^e_{k-1} = Q_e(x_{k-1}) \approx \hat{x}^e_{k-1}$$

Compute the approximation by quantizing original frame to a quality level similar to EL



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Correlation information can be estimated with low complexity

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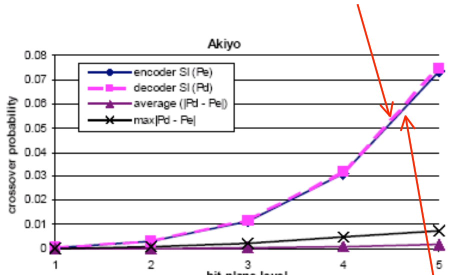
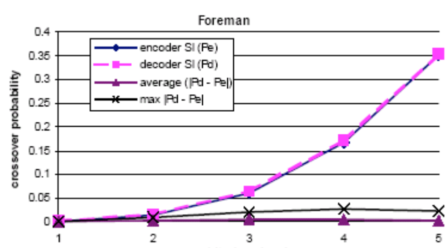
Our approximation can provide accurate statistics for DSC encoding

Correlation computed from EL reconstruction (available only at decoder)





Correlation estimated from the approximation (at encoder)

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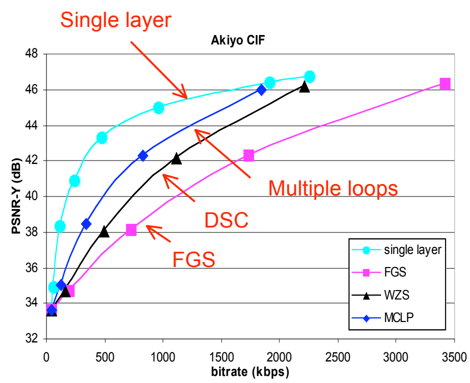
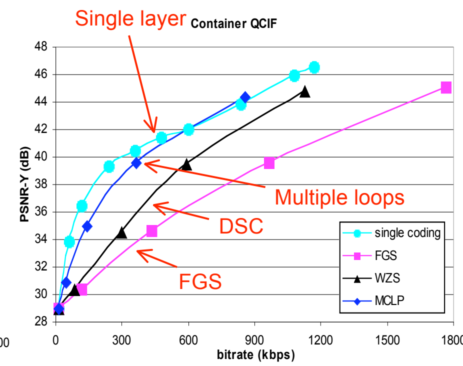
Results

Our proposed algorithm out-performs MPEG-4 FGS





Scalable Video Coding

- **Application definition**:
  - Key problem in video scalability: Multiple open loop layers (e.g.,FGS) leads to poor performance (temporal redundancy). Close loop layers require multiple reconstructions at encoder
  - Savings in terms of memory/complexity: temporal redundancy at higher layers exploited via DSC
- **Model Estimation**:
  - Temporal correlation estimated using the quantized original frame (not reconstructed one, so that EL reconstructions are not needed)
- **RD Optimization**
  - For each frame select encoding based on base layer (FGS) or temporal enhancement (WZS)

[Wang, Cheung, Ortega, EURASIP Journal on Applied Signal Proc., 2006]

DSC Application to Hyperspectral Image Coding

Case Study: Hyperspectral Imagery

- Large volume
  - Hundreds of image bands
  - More than 100M bytes per hyperspectral image
- Resource constraints
  - Encoding in satellite
  - Decoding in ground station
  - Memory, power
- High correlation between image bands

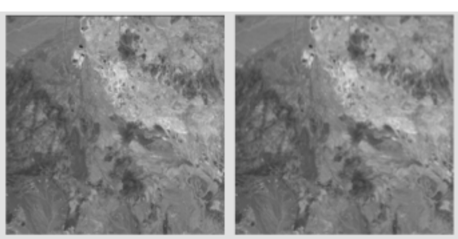
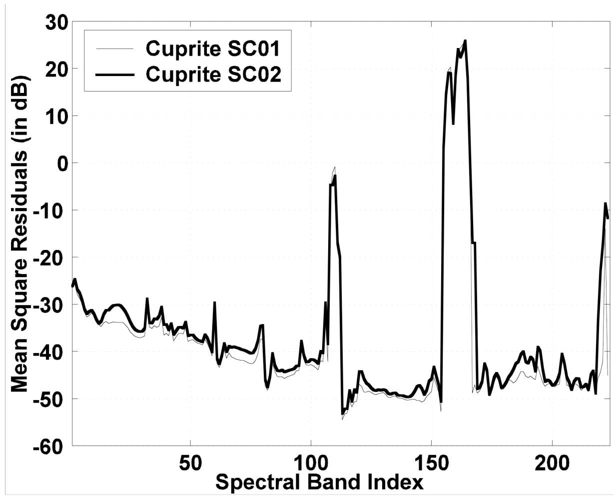


Image Band 1 Image Band 2

Inter-band Correlation



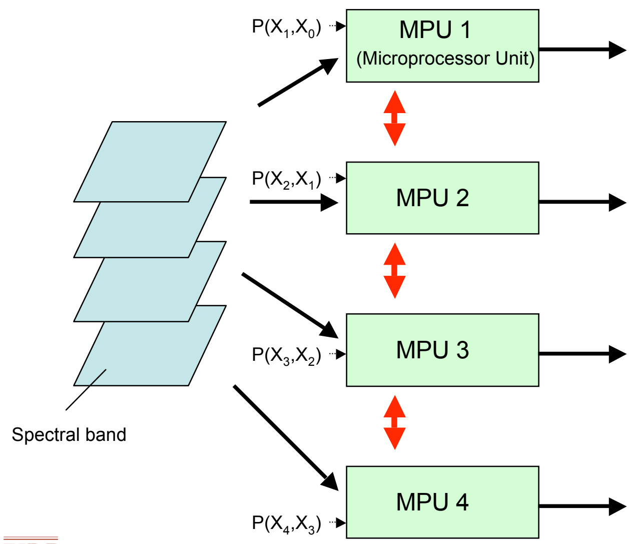
Large number of highly correlated bands; thus can achieve better compression by exploring inter-band redundancy

Approaches for Hyperspectral Imagery Compression

- Inter-band prediction approach [S.R. Tate, 1997]
  - Inherently sequential coding
  - Encoders need to perform decoding
  - Rate scalability problem
- 3D wavelets approach [X. Tang et. al., 2003]
  - Memory constraints
- Initial DSC based approach [Tang, Cheung, Ortega, Raghavendra; DCC 05]
  - Goal: parallel encoding of each band with minimum interprocessor communication

DSC Based Hyperspectral Image Compression – System Overview

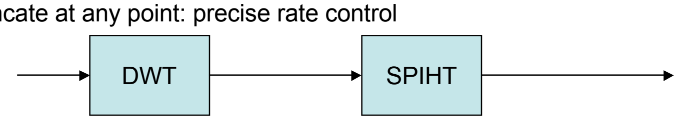
Parallel encoding

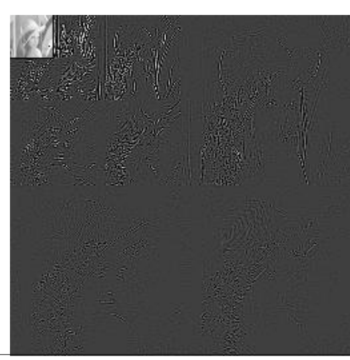


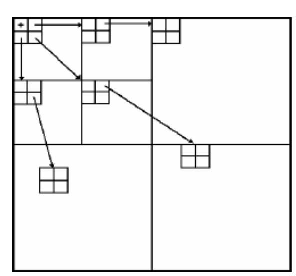
- On-board correlation estimation
  - Small amt. of data exchange
    - Inter-processors communications are slow
  - Should not hinder parallel operation
  - Low complexity

SPIHT Image Compression

- Set Partitioning in Hierarchical Trees (SPIHT, Said & Pearlman)
  - Iteratively generate **sign** and **refinement** bit-planes
  - Coefficients “partially ordered” by magnitude
  - Order information conveyed by **significance** bits
  - Truncate at any point: precise rate control



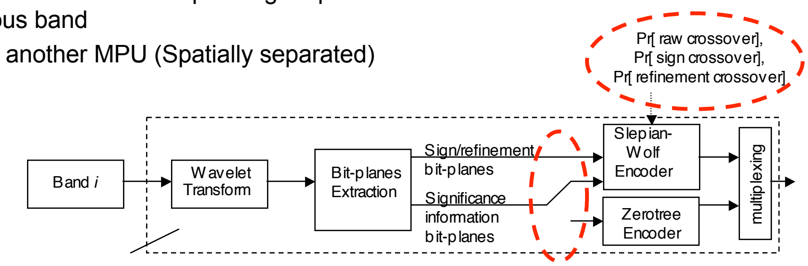




DSC Based Hyperspectral Image Compression – System Overview (Cont'd)

- Wavelet transform and bit-plane extraction
  - Sign
  - Refinement
  - Significance information
- DSC (Slepian-Wolf coding) or zerotree coding
- Side-information: corresponding bit-plane in previous band
  - In another MPU (Spatially separated)

How to estimate these crossover probabilities efficiently?



Core compression module

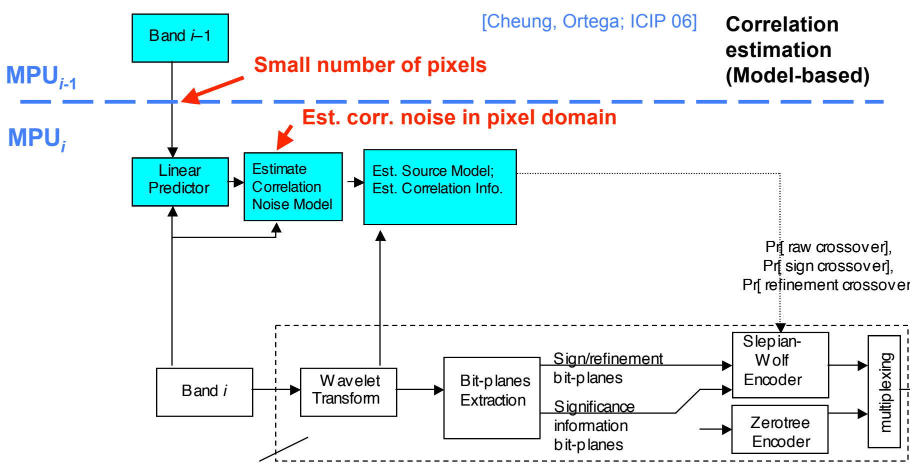
Coding strategy

[Tang, Cheung, Ortega, Raghavendra; DCC 05],
[Cheung, Tang, Ortega, Raghavendra; Signal Processing 06]

Model-based Approach to Estimate Correlation

[Cheung, Ortega; ICIP 06]

Correlation estimation (Model-based)



Core compression module

- **Lower complexity**
- **Less data traffic**
- **Improve parallelism**

Coding Summary

1. **Estimate model**: Estimate the parameters of the p.d.f. (e.g., maximum likelihood estimate) with a small percentage of pixel values exchanged (e.g., less than 5%)

2. **Derive bit-plane level statistics**: Use the estimated p.d.f. to derive the crossover probabilities analytically

3. **Determine optimal coding modes**: On which bit-planes do we apply DSC? Significance map?

Note: All these decisions can be made for each band independently, after a small number of pixels have been exchanged

1. Model Estimation

- Estimate $f_{XY}(x,y)$
  - X: Transform coefficients of current spectral band
  - Y: Transform coefficients of neighboring spectral band
- Assume $Y=X+Z$
  - Z is the correlation noise independent of X
- Factor $f_{XY}(x,y) = f_X(x)\, f_Z(y-x)$
  - $f_X(x)$: source model
  - $f_Z(z)$: correlation noise model
- Estimate $f_X(x)$, $f_Z(z)$ with different procedures

2 Derive Bit-plane Crossover Probability

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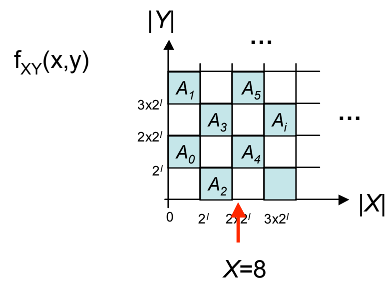
- Derive estimate of p_l (Given $f_{XY}(x,y)$)
- **Crossover (of raw bit-planes) corresponds to regions A_i**
- Example: l=2; X=8
- Crossover probability estimate:



$$\hat{p}_l = \sum \iint_{A_i} f_{XY}(x,y)dxdy$$

- In practice, only need to sum over a few regions

X=8

		Y: 0	1	2	3	4	5	6	7	8	9	…
msb	1	0	0	0	0	0	0	0	0	1	1	1 1
→	0	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**1**	**0**	**0**	**0 0**
	0	0	0	1	1	0	0	1	1	0	0	1 1
	0	0	1	0	1	0	1	0	1	0	1	0 1

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3. Coding Strategy

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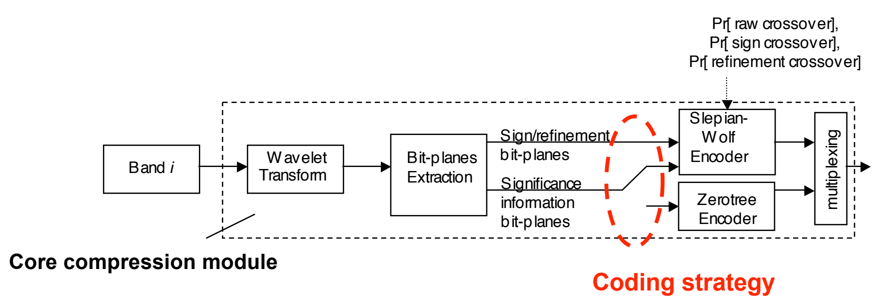
- Different types of bit-planes
  - Sign
  - Refinement
  - Significance map
  - Raw
- DSC (inter-band coding) or zerotree (intra) coding?



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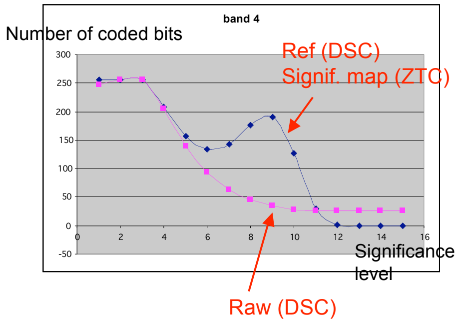
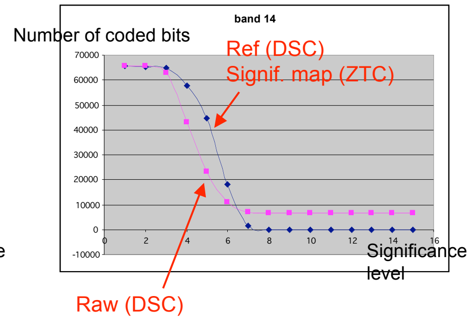
Modeling Results

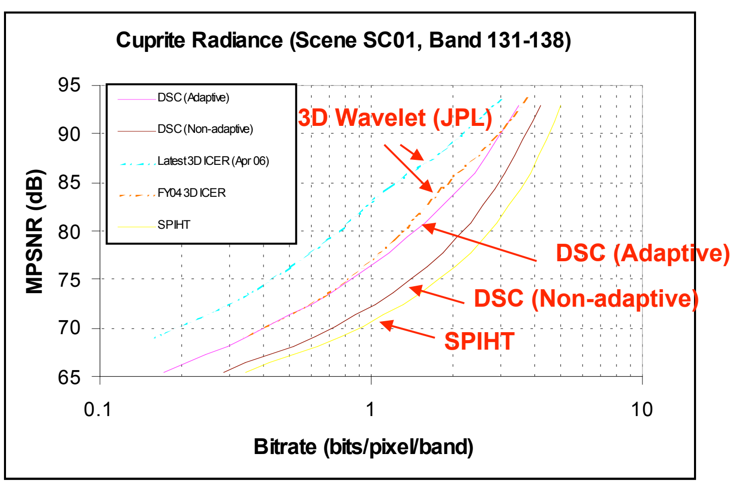




- At high significance levels, better results by compressing the signif. map using ZTC
- In the middle range, coding the entire raw BP with DSC can achieve better result
- For least signif. BP, both cannot achieve much compression

Results

- Compared DSC-based system with and without adaptive coding
  - Non-adaptive: compress signif. map with ZTC for all levels
- Compared with 3D Wavelet based systems
  - 3D ICER from NASA JPL [Kiely, Klimesh, Xie, Aranki; 2006]



Hyperspectral Image Coding

- **Application definition**: Multiprocessor system, spectral bands processed by different processors, exploit inter-band correlation with minimum inter-processor communications
  - Savings: Reduced communication between processors.
- **Modeling**:
  - Crossband correlation in the bitplane domain, estimated using pixel-domain correlation approximated as i.i.d., using exchanged pixels
- **RD Optimization**:
  - Choice between DSC coding of refinement bits only or of raw bits

[Cheung, Tang, Ortega, Raghavendra, Signal Processing, 2006]
[Cheung, Wang, Ortega, IEEE Transactions on IP, 2008, to appear]

DSC Application to Flexible Video Decoding

Free viewpoint switching poses challenges to multiview compression

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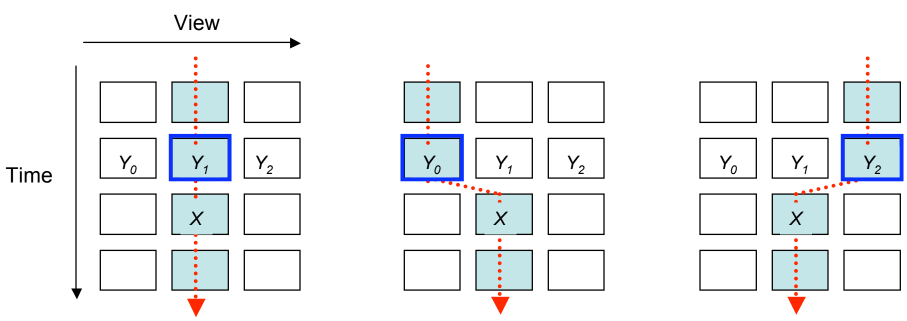
When users can choose among different decoding paths, it is not clear which previous reconstructed frame will be available to use in the decoding



Multiple decoding paths ⇨ Either Y_0 or Y_1 or Y_2 will be available at decoder ⇨ Uncertainty on predictor status at decoder!

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Problem Formulation

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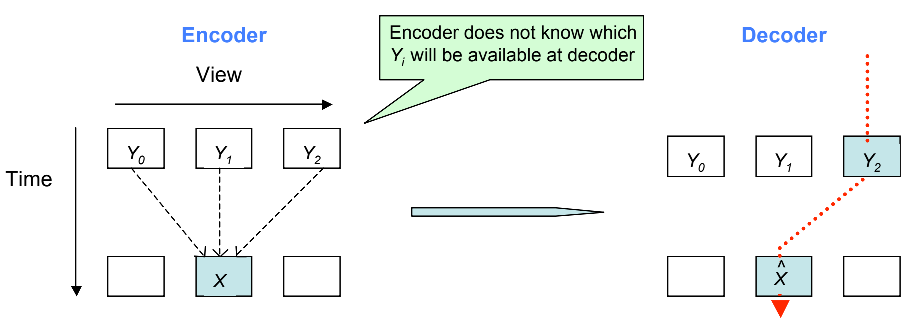
To support low-delay free viewpoint switching (flexible decoding), encoder needs to operate under uncertainty on decoder predictor
[Cheung, Ortega; MMSP 07]



- Assume feedback is not available
  - Low-delay, interactive application
  - Offline encoding of multiview data

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Other Flexible Decoding Examples – Forward/Backward Frame-by-frame Video Playback

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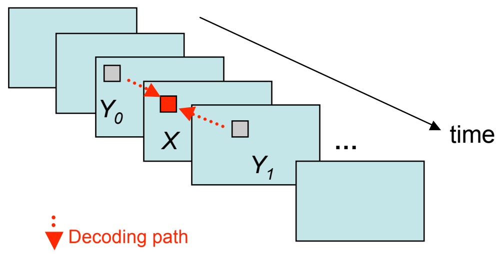
[Cheung, Wang, Ortega; VCIP 06]

User can choose to play back in either direction:
Either past **or** future reconstructed frame will be available at decoder



Y_0, Y_1: best motion-compensated predictor for X

- Not B-frame (as in video coding standards)
- Not multiple reference frames

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Other Flexible Decoding Examples – Robust Video Transmission

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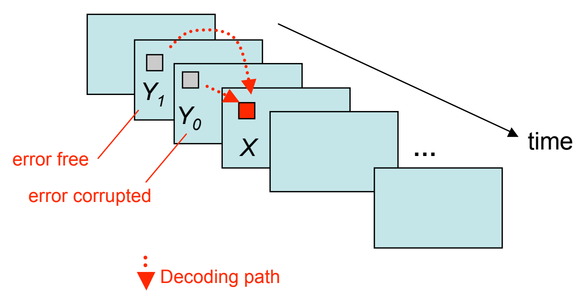
[Wang, Prabhakaran, Ramchandran; ICIP 06]



Some reference frames have error, but encoder does not know which one (assume feedback is not available)

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Address Viewpoint Switching/Flexible Decoding Within Closed-Loop Predictive (CLP) Coding Framework

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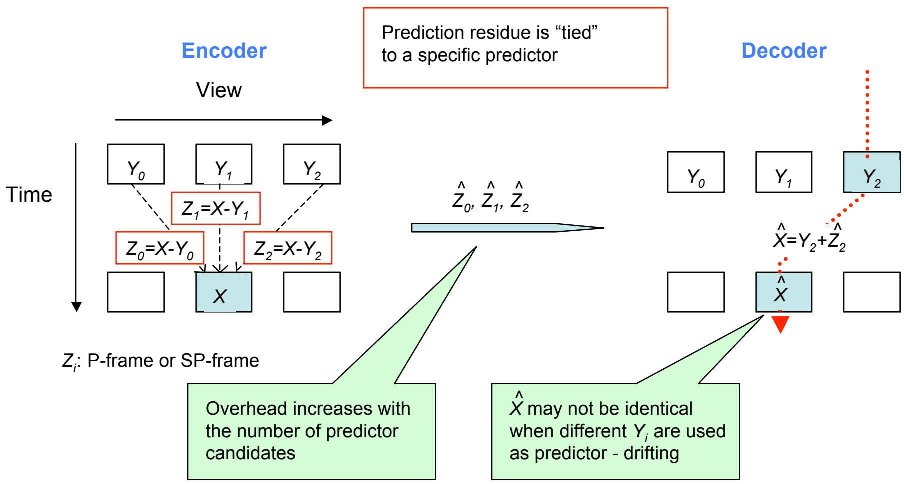
Encoder has to send **multiple** prediction residues to the decoder



DSC - Virtual Communication Channel Perspective

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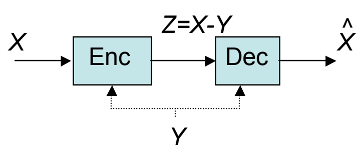
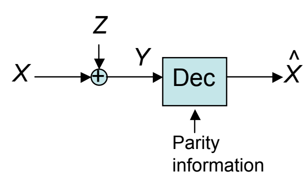
In DSC, encoder can communicate X by sending **parity information**
(E.g., [Girod, Aaron, Rane, Rebollo-Mondero; Proc. IEEE 04])

CLP:

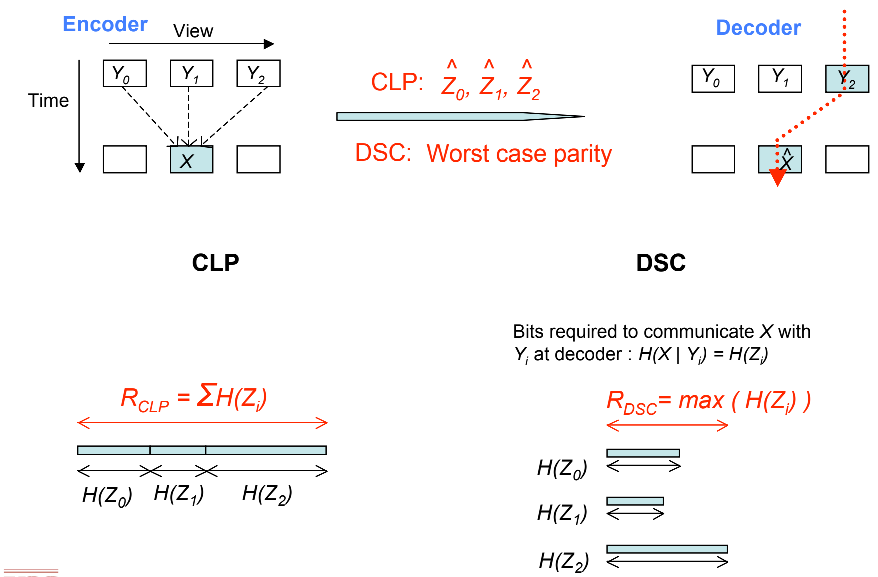


DSC:



Parity information is **independent** of a specific predictor
- What matters is the **amount** of parity information

Viewpoint Switching (Flexible Decoding): CLP vs. DSC



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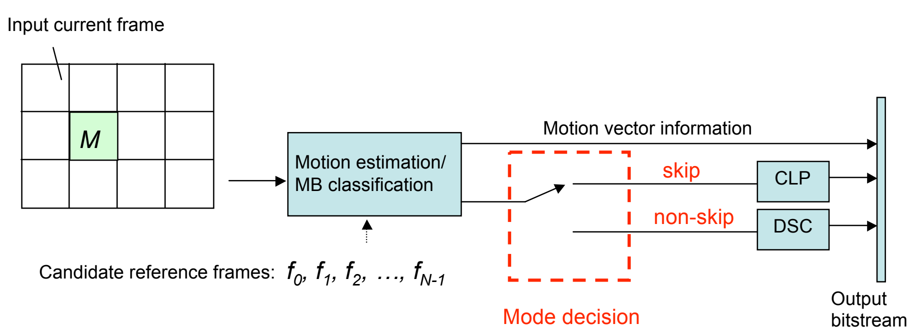
Encoding Algorithm – Motion Estimation and Macroblock Classification

M may be classified to be in a *skip* mode if the difference between *M* and predictors from some f_i is small



Majority: using DSC
Also: send Intra if more efficient

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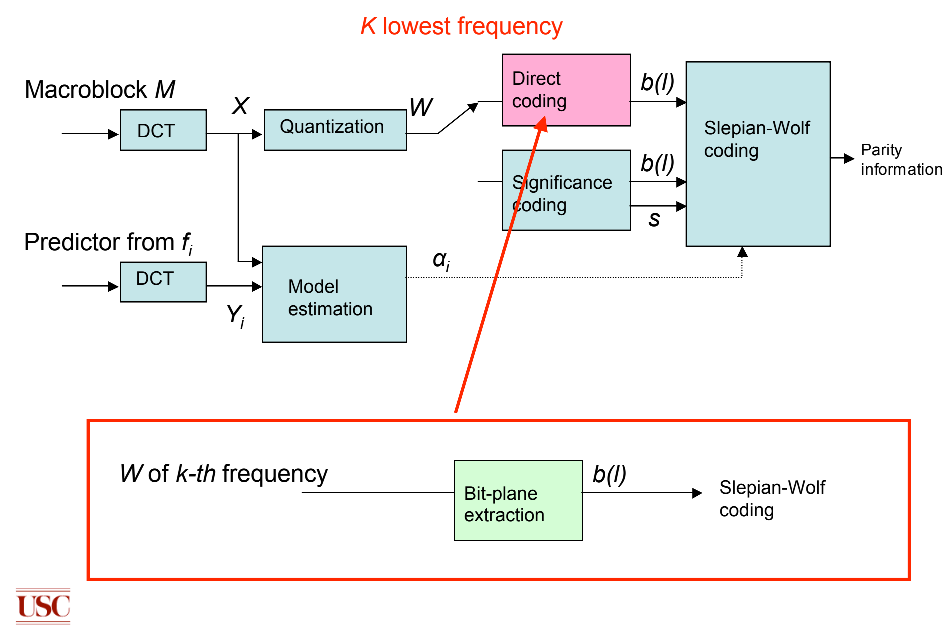
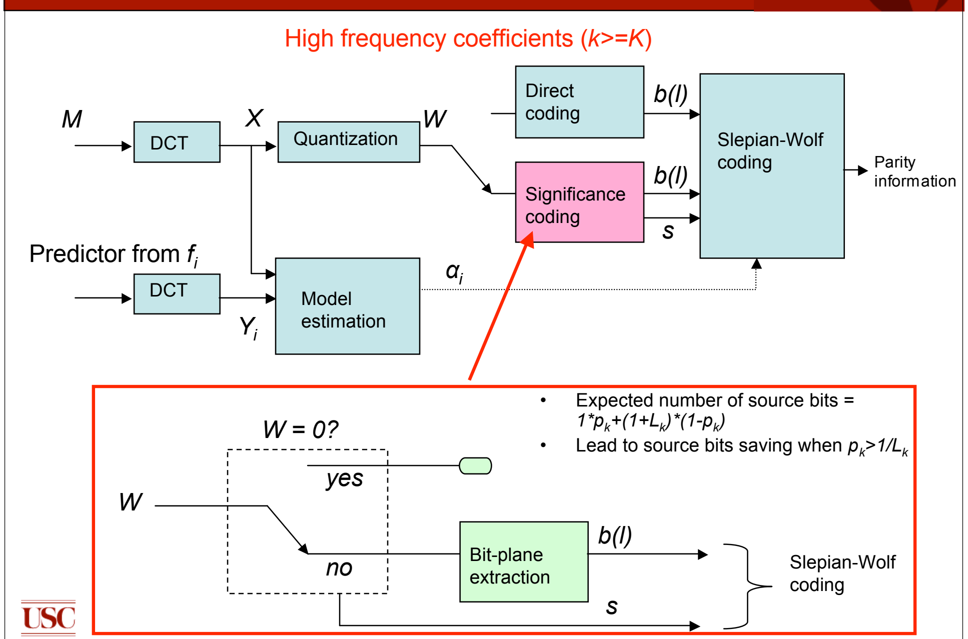
Encoding Algorithm – DSC Coded MB

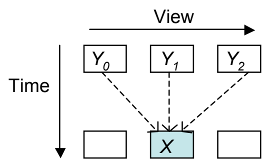


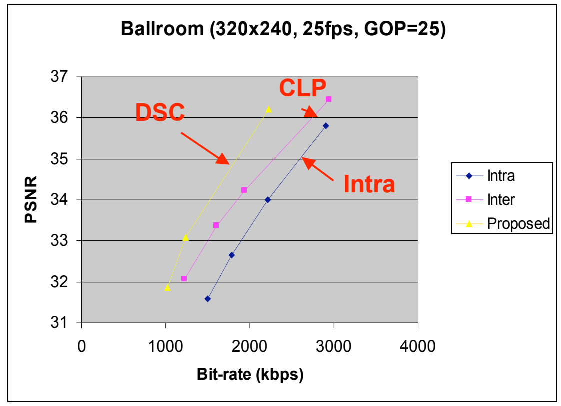
Encoding Algorithm – Significance Coding



Experimental Results - Multiview Video Coding

Allow switching from adjacent views: three predictor candidates





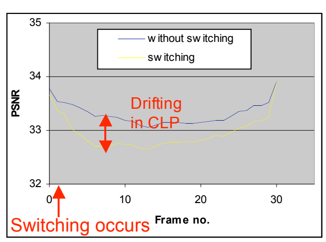
Our proposed algorithm out-performs CLP and intra coding

Drifting Experiments

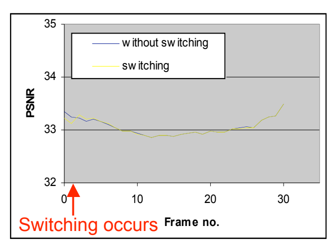
Our proposed algorithm is almost drift-free, since quantized coefficients in DSC coded MB are identically reconstructed

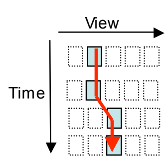
Akko&Kayo (GOP=30)

CLP



DSC





View switching occurs at frame number 2

Scaling Experiments

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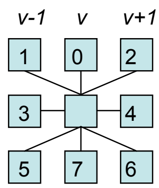
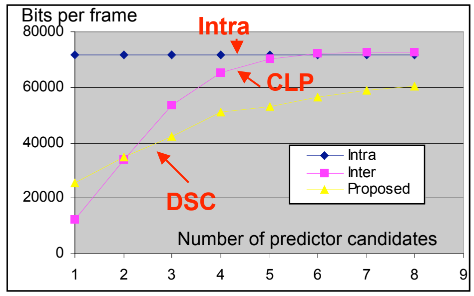
- Number of coded bits vs. number of predictor candidates





- Bit-rate of DSC-based approach increases at a slower rate compared with CLP
  - An additional candidate incurs more bits only if it has the worst correlation among all candidates

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Experimental Results – Forward/backward video playback

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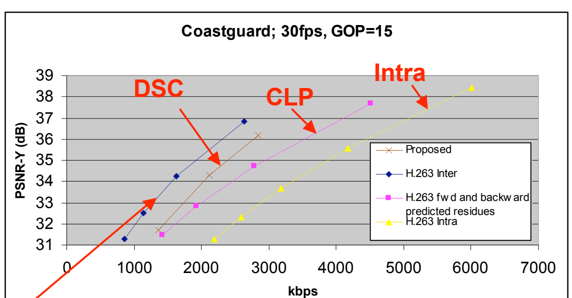
Forward/backward playback: **two** predictor candidates



Coastguard CIF

Inter-frame coding with one prediction residue: cannot support flexible decoding

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Flexible Video Coding

- **Application definition**: Exploit temporal correlation between frames, where one among a known set of frames is used as side information
  - Savings: Better RD performance than methods that send all possible residues.
- **Modeling**:
  - Worst case "noise" between data to be sent and all candidate predictors.
- **RD Optimization**:
  - Mode selection tools
- For more details:

[Cheung, Ortega, MMSP 2007, PCS 2007, VCIP 2008]

Conclusions

- **Potential of DSC for interesting applications**
- **Application definition**:
  - Careful definition/quantification of expected gains in terms of another metric of interest (lower memory, parallelism, flexibility, etc)
- **Modeling**:
  - Probability models are never "given". What is a good model in terms of explaining the data while also being easy to estimate without affecting RD and other metrics.
- **RD Optimization**:
  - Alternative metrics are useful, but it is RD performance that will "sell" a coding system