



### The Future of Image Compression

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### Outline

- Where are we?
- Data handling trends
- Improvements? Breakthroughs?
- Conclusions





## Efficiency of Modern Methods

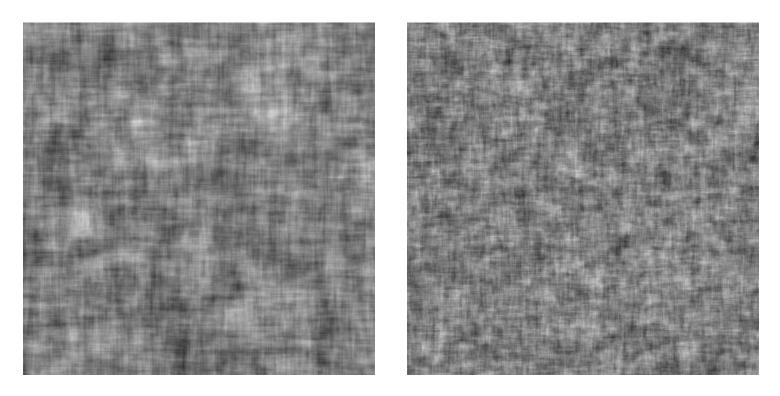
- Methodology
  - Generate Gauss-Markov Images
  - Compare compression results with Rate-Distortion or joint entropy function





### Gauss-Markov Images

Variance = 400 Mean = 128



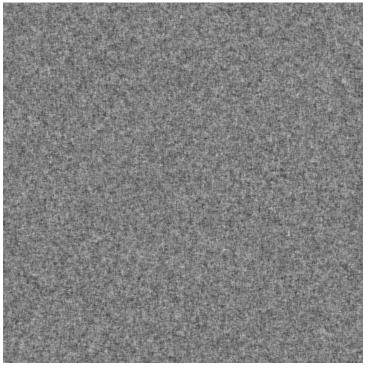
a = 0.95

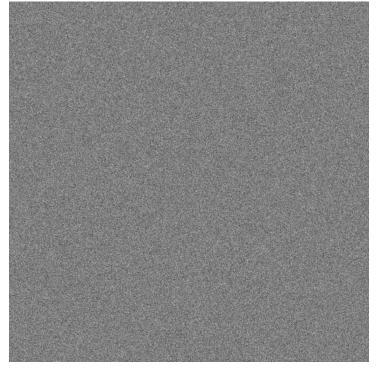
a = 0.90

Separable; 8-bit precision; 512x512 lower cut from 640x640



Variance = 400 Mean = 128









Separable; 8-bit precision; 512x512 lower cut from 640x640





### **Theoretical Bounds**

Rate-Distortion Function (Gaussian, squared error)

$$R = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \max\left\{0, \frac{1}{2} \log_2 \frac{\lambda(i)\lambda(j)}{\theta}\right\}$$
$$D = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \min\left\{\theta, \lambda(i)\lambda(j)\right\}$$

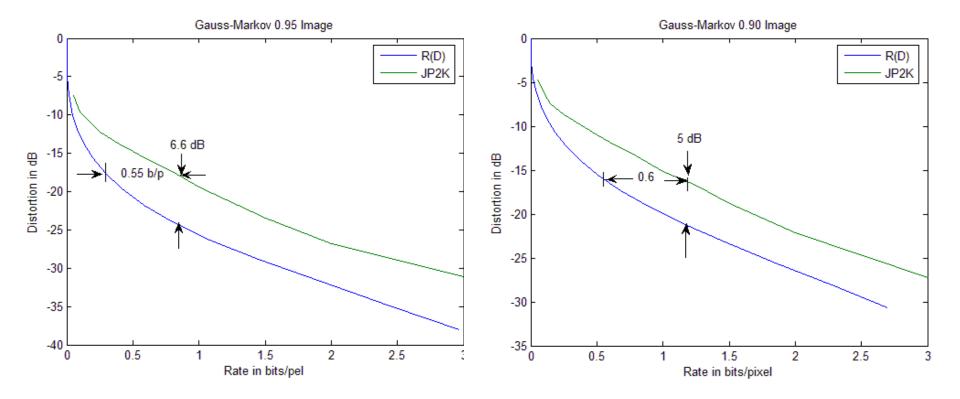
Approximate Gaussian Entropy Function Using  $H(X^n) \approx h(X^n) - \log_2 \delta$   $-\log_2 \delta = m$  bits (precision)  $\frac{1}{N^2} H(X^{N^2}) \approx \frac{1}{2N^2} \sum_{i=1}^N \sum_{j=1}^N \log_2(\lambda(i)\lambda(j)) + \frac{1}{2}\log_2 2\pi e \sigma_X^2 + \frac{m}{N^2}$ 

(Eigenvalues normalized for unit variance)





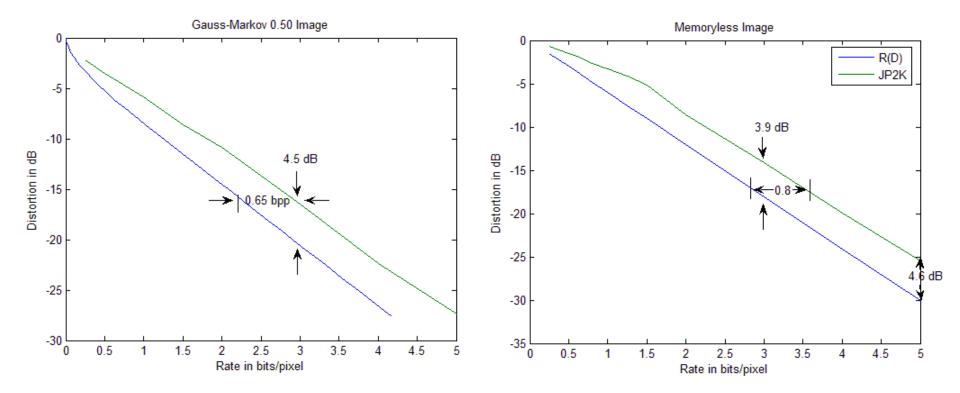
### Comparisons







### **More Comparisons**







### **Lossless Compression**

		Differences from Entropy (b/p)		
Correlation Parameter	Joint Entropy (b/p)	SPIHT	CALIC	JP2K
0.95	3.0172	0.9438	0.4188	0.4838
0.90	3.9778	0.6652	0.2312	0.3762
0.50	5.9548	0.2392	0.0872	0.3172
0	6.3691	0.2469	0.1779	0.3639

\* CALIC closest to entropy in all cases

\* JP2K beats SPIHT above a = 0.5, but worse otherwise





### What Have We Learned?

- Much room for improvement for lossy compression :
  - > 0.5 bpp for high quality
  - 4 to 6 dB at useful bit rates
- Small room for improvement for lossless compression - ~0.2 bpp
- \*\*Lesson: The best adaptive techniques can take you only so far.





### Where to go from here?

- For pure compression, much more potential payoff for lossy methods.
- Clearly advantageous to transform to independent variables and/or segment to stationary entities.
  - closes performance to the latter gaps
- Barring advancements in pure compression, need to pursue
  - better transforms that are adaptive to image features
    - Bandelets, curvelets, etc. ?
  - better segmentation methods





### **Technology Advances**

- Dramatic increases in processor speeds seem to be ending
  - Parallelization by multi-core processor chips is the trend
  - New parallel forms of algorithms for compression likely to emerge
    - Currently JPEG2000 and JPEG have parallel structure --- nothing new here
- More compact, higher power batteries would expand application scenarios for compression
- Miniaturization to quantum limit to be reached in 10 to 15 years
  - Quantum Computers





### **Future Application Space**

- Large images with multiple dimensions
  - Examples:
    - 4 dimensions: fMRI, medical ultrasound view
    - Materials micro-structures with many attributes at given grid point.
- Content-based retrieval from large databases
  - Internet application needs interactivity for consultation and quantitative analysis.
  - Need fast search and retrieval and fast scalable decoding for browsing, retrieval, and transmission
    - Places limits on complexity and memory usage
      - Increase in size always seems to outpace gains in speed
    - Not likely to close existing performance gaps with simpler techniques that utilize less memory.
      - Fruitful or fruitless pursuit?
    - Contribution is to limit degradation the least possible by being clever





### Example: Retrieval from Large Multi-D Images

Click on file name in web site and left image appears.

Right image appears using ROI Menu and mouse Selection of region

Any slice can be viewed by dropping Frame menu and entering number

In View menu, can select Full volume and ROI views In 3-D -- see next slide

Micro-structure

# D3D Viewer Quality Resolution Frame ROI Help Edit View 167 MB $\rightarrow$ 4 MB compressed 41:1 Ready

#### Communication/Display GUI

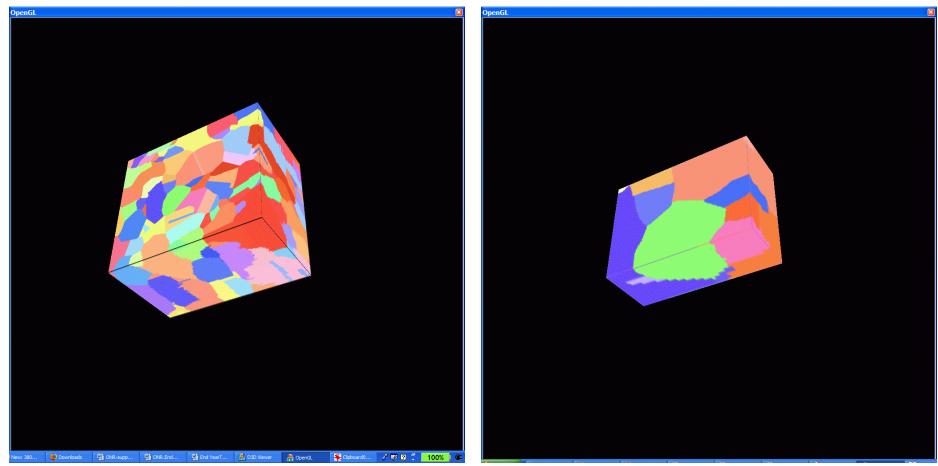




### **3-D** Views

#### Full volume

#### ROI

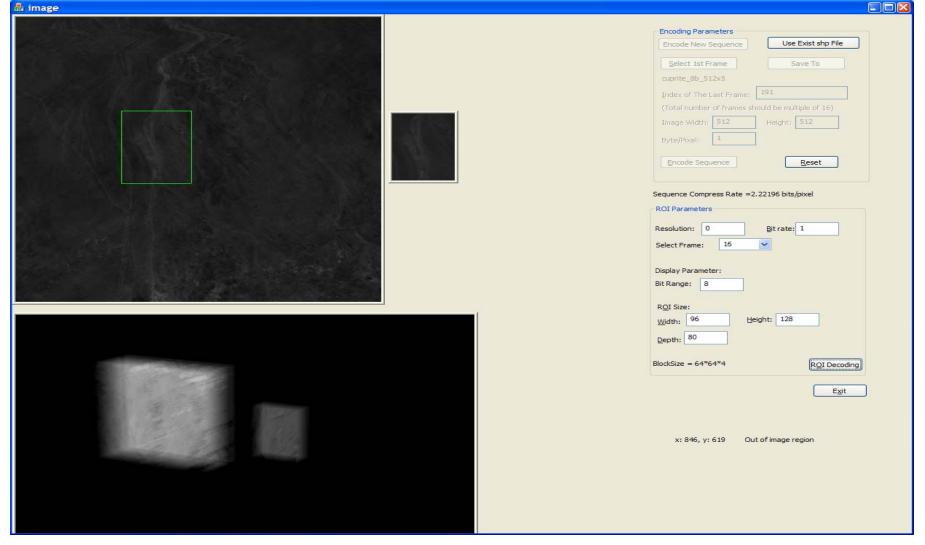


#### Rotation by mouse manipulation





#### Hyperspectral Images

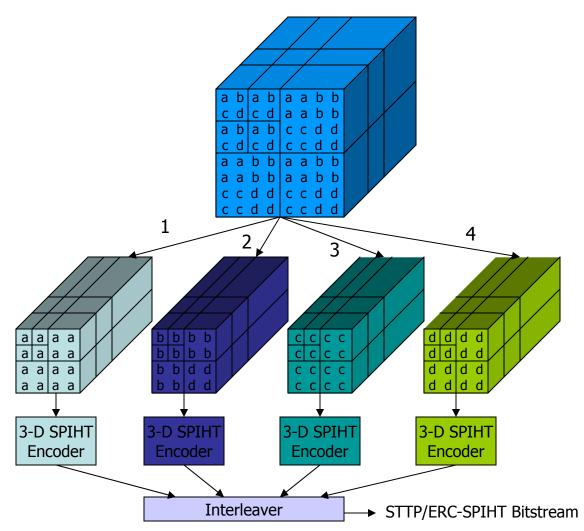








### **Multiple Description Coding**



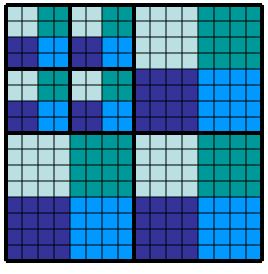
- S sub-bitstreams are interleaved in appropriate size units (e.g. bits, bytes, packets, etc.)
- Embedded nature is maintained
- We can stop decoding at any compressed file size
- May transmit subbitstreams separately over MIMO channel



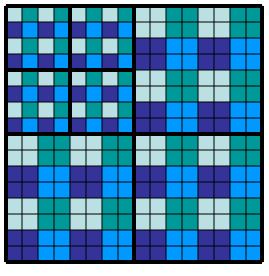


### **Grouping Methods**

\* 16x16 image with 2 level decomposition, and *S*=4



Contiguous Grouping



**Dispersive Grouping** 

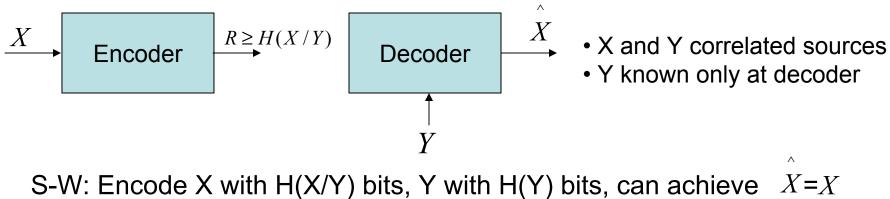
- o Extensible to larger dimensions
- o Compatible with parallel architectures
- o Follows natural order of coding for tree-based methods: on-the-fly transmission
- o Fits well into W-Z or S-W paradigm





### **Distributed Source Coding**

Source Coding with Side Information: Slepian-Wolf 1973, Wyner-Ziv 1976



No loss of performance over when Y is known at encoder also, if statistics X given Y are known.

W-Z: Lossy coding performance same whether Y is known at both ends or only at decoder, *if statistics of X and Y are jointly Gaussian*.

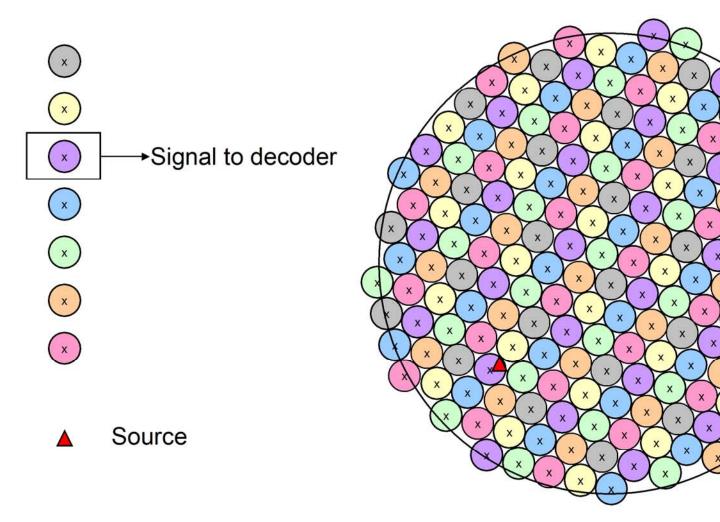




### **Promising Realization**

- Encoder of X sends index of coset (syndrome bits of channel code)
- Decoder uses Y and coset index to estimate X.

#### Example: geometric illustration



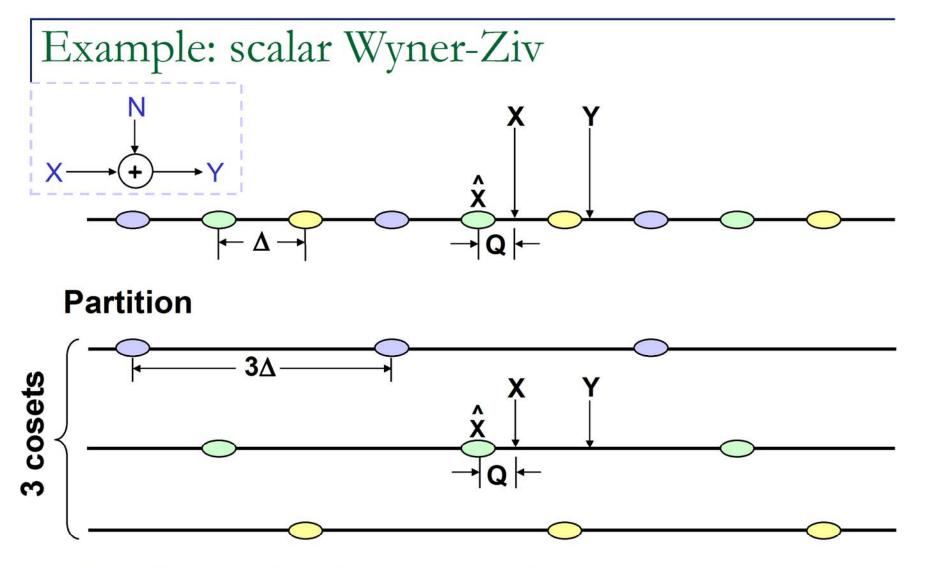
Assume signal and noise are Gaussian, iid

Figure courtesy of K. Ramchandran

#### Example: geometric illustration х X х x х x х х х х х х х х x х х х х х х Source Side information х

Assume signal and noise are Gaussian, iid

Figure courtesy of K. Ramchandran



- Encoder: send the index of the coset (log<sub>2</sub>3 bits)
- Decoder: decode X based on Y and signaled coset





### **DSC Image Compression Scenarios**

- Low complexity encoding for image transmission
- Sensor networks
  Multiview coding
- Multiple description coding
- Camera alignment
- Cryptogram compression
- None likely to bridge identified performance gaps, especially for the usual non-Gaussian lossy coding





### **Quantum Computing**

- Quantum computers can solve some math problems considerably faster than classical computers
- Qbit(.com) claims 2-10:1 lossless image compression at 1.5 Gbits/sec throughput with qubit processor? US 2004/0086038 App.
- Quantum Information Theory
  - Well developed; parallels Shannon theory
    - Source coding theorem (von Neumann entropy limit)
    - R(D) theorem
    - S-W and W-Z theorems
    - Channel capacity theorem





### Quantum Bits and Entanglement

• General state of one qubit (input):  $\alpha$  's complex

$$|\psi\rangle = \alpha_0 |0\rangle + \alpha_1 |1\rangle$$
,  $|\alpha_0|^2 = \Pr\{|0\rangle\}$   $|\alpha_1|^2 = \Pr\{|1\rangle\}$ ,  $|\alpha_0|^2 + |\alpha_1|^2 = 1$ 

- said to be *entangled* Ex.: photon  $|\psi\rangle = (1/\sqrt{2})|0\rangle + (1/\sqrt{2})|1\rangle$  linear polarized at 45°
- Output is measurement:  $|0\rangle$  or  $|1\rangle$ 
  - Orthogonal states can be measured
  - Similarly for 2-qubit system- states are entangled

$$\psi\rangle = \alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|10\rangle + \alpha_{11}|11\rangle$$

- *n-qubit space 2<sup>n</sup> dimensional Hilbert Space*
- States can not be copied or cloned.
- A measurement changes the state: basis of secure key distribution
- States can be communicated





### Entropy Example

Two equiprobable photon states: Shannon entropy = 1 bit Suppose  $0 \rightarrow |0\rangle$  H polarization Suppose  $1 \rightarrow \psi = \cos \theta |0\rangle + \sin \theta |1\rangle$  Angle  $\theta$  polarization

Von Neumann Entropy S( $|0\rangle$ ,  $\psi$ ) =  $H_2((1-\cos\theta)/2)$ Binary entropy function  $H_2(p) = -p \log_2 p - (1-p) \log_2(1-p)$ 

Except for  $\theta = \pm \pi / 2$  ,  $S(|0\rangle, \psi) < 1$ 

But, only  $\theta = \pm \pi / 2$  is detectable !!

Therefore, von Neumann entropy may have no realizable association to information.





### **Prospect of Lower Compression Limit**

- So far, quantum information theory does not give physically realizable lower entropy limits
- Also, the devices and detectors work only in the laboratory or with limited capability polarizers,1-qubit gates, and short shift registers
- Short error-correcting codes, secure key distribution
- Physicists are hard at work to make the devices that form specified quantum states
- Physicists have taken the lead at formulating quantum information theory, but our community has been roused (e.g., Devetak & Berger, "Quantum R-D Theory," Trans. IT Jun 2002; Rob Calderbank)
- Further reading
  - M. A. Nielson, I. L. Chang: Quantum Computation and Quantum Information
  - N. D. Mermin : Quantum Computer Science: An Introduction
  - J. Audretsch, Ed.: *Entangled World: The Fascination of Quantum Information and Computation*
  - Bennett & Shor, "Quantum Information Theory", Trans IT, Oct 1998





## Conclusion

- Substantial gaps to compression limits still exist
- Trend toward algorithms to handle large, multidimensional images
- Trend to multiple core processors to spur development of new parallel processing paradigms
- Open question whether quantum information theory and quantum computation will save the day





# Thank you!