Technion-Israel Institute of Technology
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Image Palettization and Compression for Color-Limited Displays

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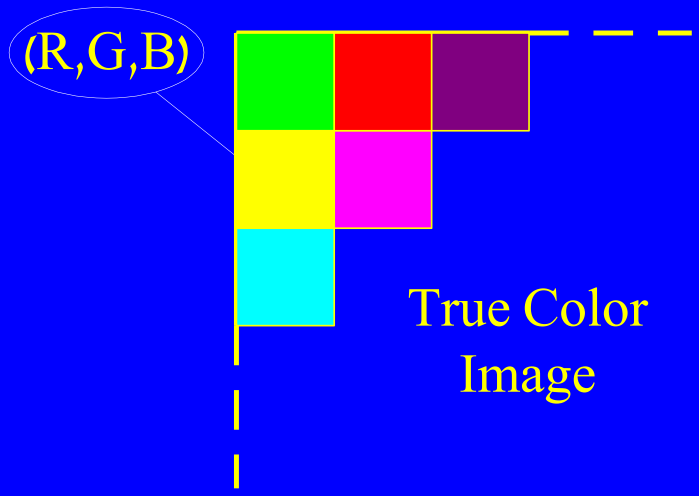
True Color image vs. Indexed image

- For indexed images, the max. number of colors displayed simultaneously is restricted by palette size
- For less colors, the two kinds of images are visually identical



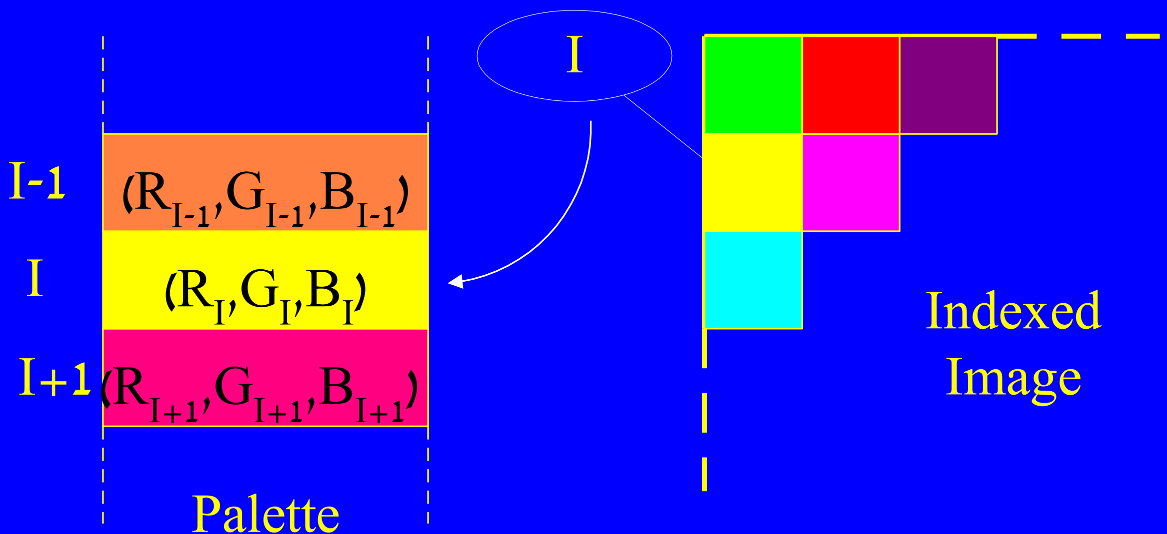


Image compression methods used for the Internet

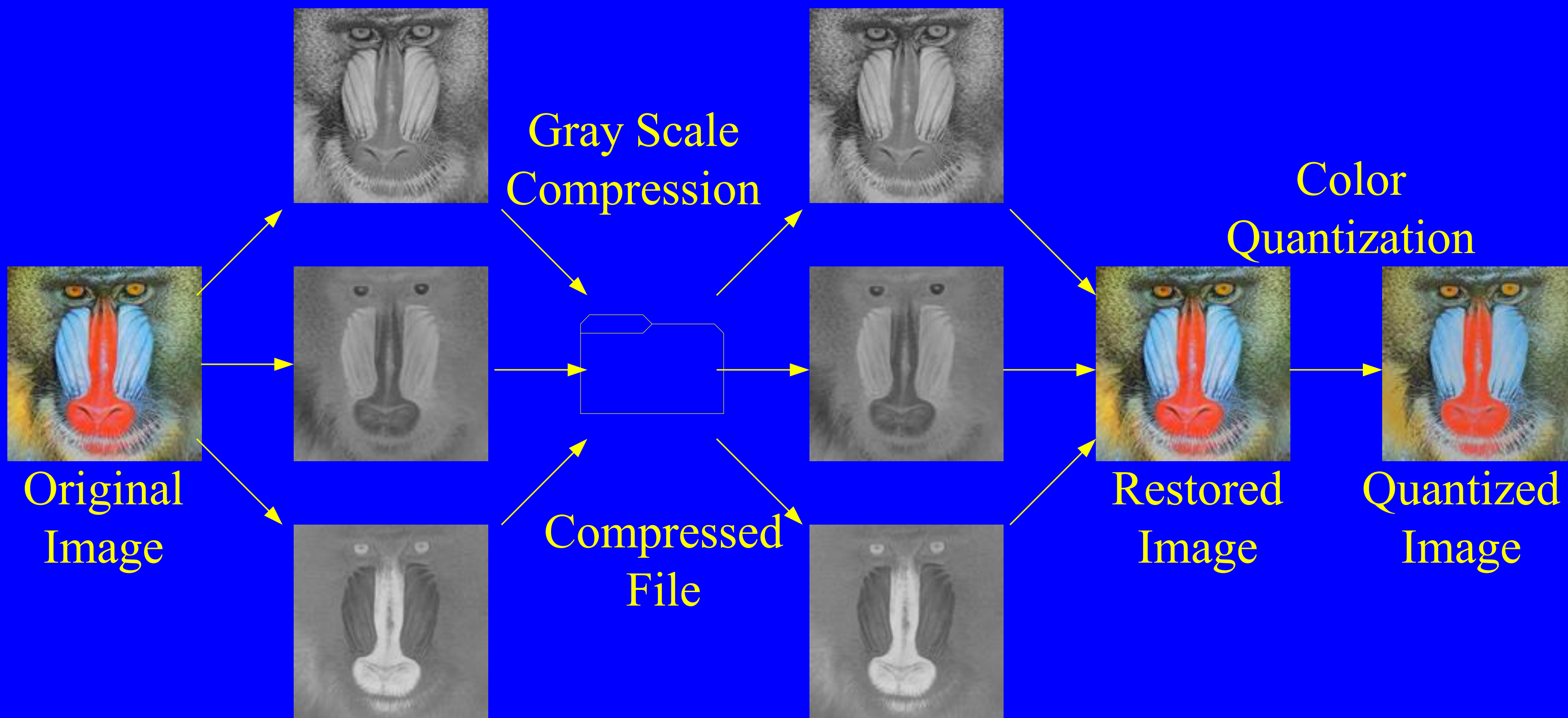
JPEG (natural images)

- Lossy mode (DCT, quantization, zig-zag scan, Huffman coding)
- Lossless mode - LOCO (predictor, context-based Golumb-Rice coding)

GIF (max. 256 colors, typically Line Art)

- Lossless mode (Raster scan, LZW coding)

Common method for indexed images



No consideration for the receiving display

Drawbacks of the common method

- Computational Complexity

  Color Quantization (CQ) is computationally complex

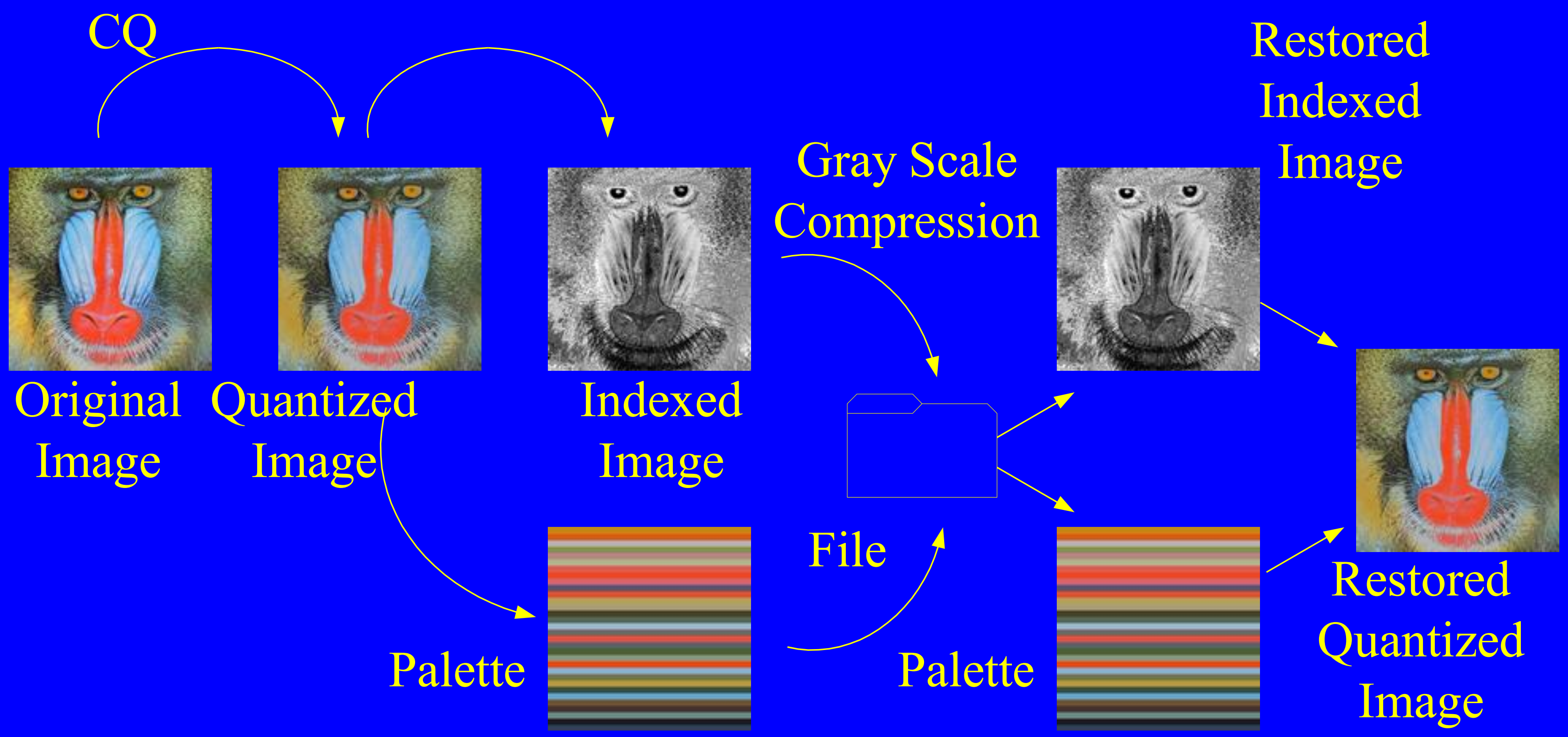
  The sending side is usually computationally superior to the receiving side

  The receiving side should work in real time

- Compressibility

  An Indexed image has less bits to begin with

The proposed method



Presentation Overview

- Color Quantization
- Color Ordering
- Lossless Compression of Natural Indexed Images
- Lossy Compression of Natural Indexed Images
- Lossy Compression of Hyperspectral Images
- Index Assignment

Color Quantization

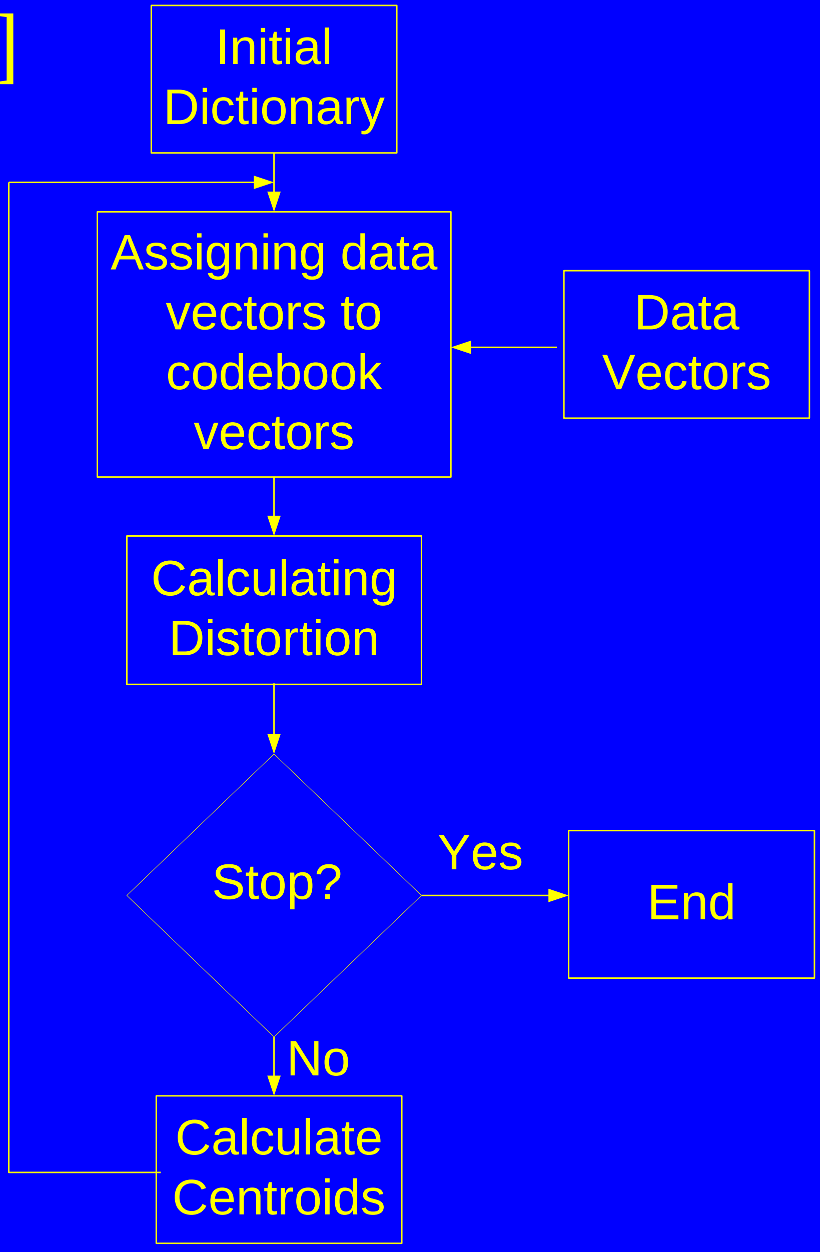
NP-Complete problem with sub-optimal solutions (simple and good for real time):

- Popularity Algorithm, Median Cut [Heckbert, 1982]
- MaxMin Algorithm [Houle et al., 1986]
- Improved Popularity Algorithm [Braudaway, 1986]
- Mean Split [Gentile et al., 1990]
- Variance-based [Wan et al., 1990]
- Tree-based approach [Orchard et al., 1991]

LBG [Linde et al., 1980]

A Vector Quantization (VQ) method that iteratively runs the Generalized Lloyd (GL) algorithm, each Iteration doubling the size of the dictionary

The GL algorithm



LBG (cont'd)

Color Spaces:

Tested for 3 different color spaces:

- RGB (simple)
- YCbCr (more in accordance to the HVS)
- Lab (HVS compatible, uniform, takes into account Just Noticeable Difference)

Lab gave significantly better results

Dithering:

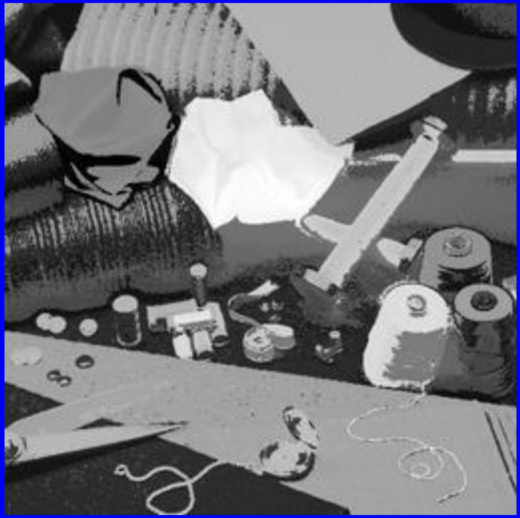
No dithering used

LBG (cont'd)

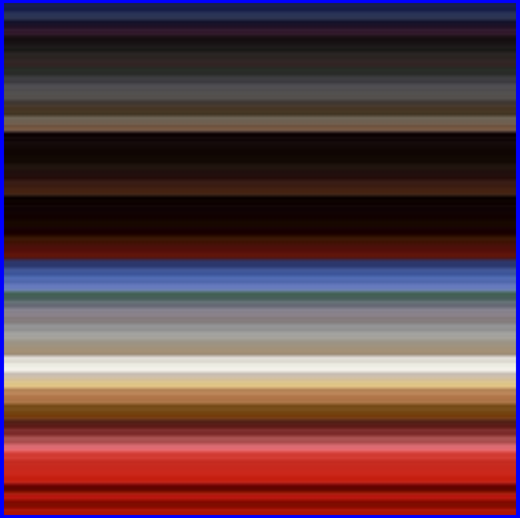
Original Image

Quantized Image (256 colors)

Indexed Image



Palette



Color Ordering

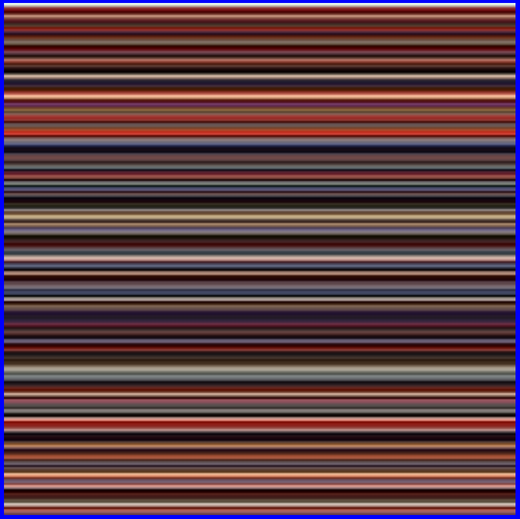
Ordering the colors in the palette so that close indices represent visually similar colors

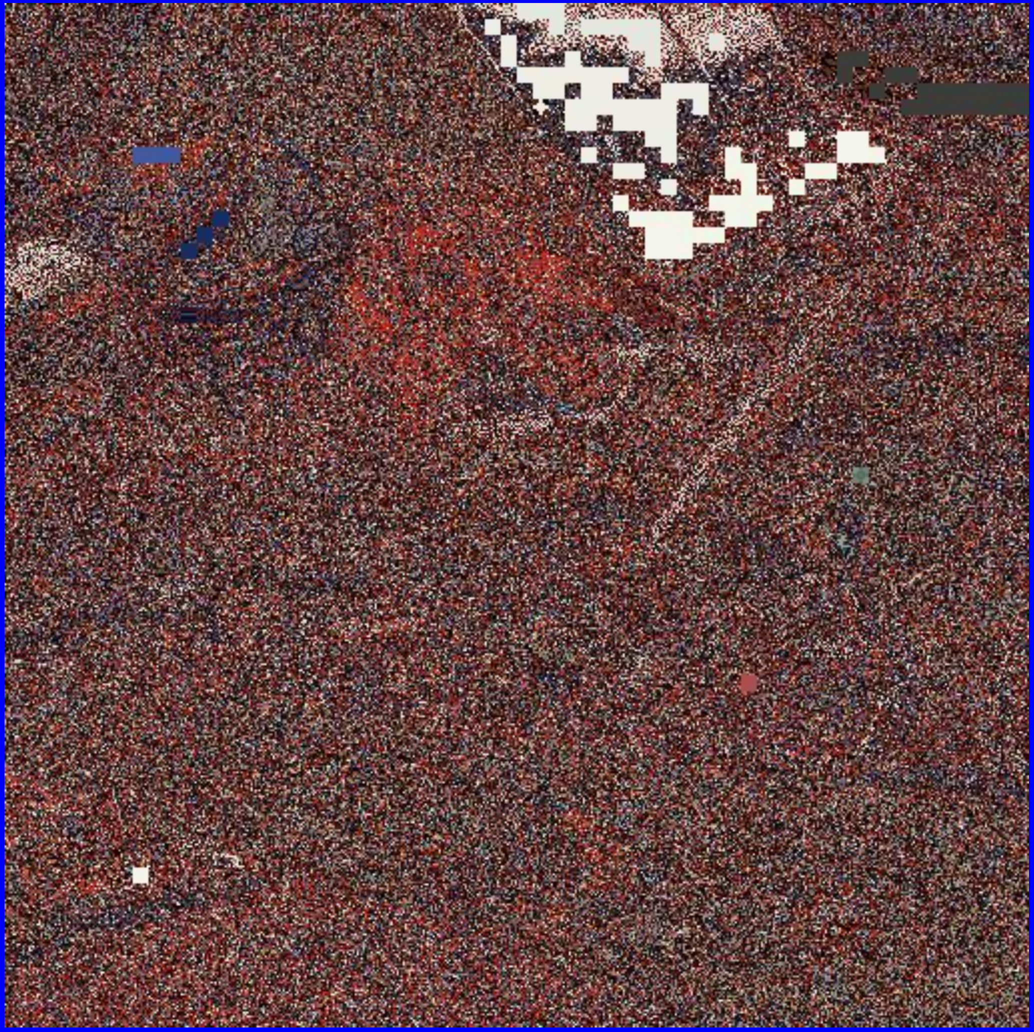
<u>What for</u>?

1. Reconstruction errors in lossy compression

2. Compression ratio (due to spatial correlation)

Reconstruction of a coded random-ordered indexed image





Binary Switching Algorithm (BSA) [Zeger et. al., 1990]

Originally used for Index Assignment and modified for our purposes

Initialization:

$c_i \ , i = 1, \ldots N$ - initial palette

$$D = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} d(c_i, c_j) p(i \to j)$$ - distortion function

$p(i \to j)$ - probability of index change due to compression

$d(c_i, c_j)$ - color distance function

BSA (cont'd)

Empirical probability model of index change:

$$p(i \to j) = \begin{cases} c\left(1 - \frac{|i-j|}{w}\right) & |i-j| \le w \\ 0 & otherwise \end{cases}$$

w- region of influence's width

c - normalizing factor

<u>Iterations</u>:

- Select color causing max. distortion
- Switch its index with another to minimize distortion

Good results, but very demanding computationally

Multidimensional Scaling (MDS)
Sammon's Mapping [Sammon, 1969]

Used to find a distance-preserving projection of a set of vectors to a space of smaller dimension

<u>Initialization</u>:

$x_i\ ,\ i = 1, \ldots N$ - k_1-dimensional vectors

$\boldsymbol{T}$ - sought after k_2xk_1 projection matrix

$d(x_i, x_j) = \sqrt{\sum_{k=1}^{k_1} \left(x_i^k - x_j^k\right)^2}$ - distance function in original space

$\tilde{d}(x_i, x_j) = \sqrt{\sum_{k=1}^{k_2} \left[(Tx_i)^k - (Tx_j)^k\right]^2}$ - distance function in projected space

MDS (cont'd)

$$F(T)=\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\frac{\left[d(x_i,x_j)-\tilde{d}(x_i,x_j)\right]^2}{d(x_i,x_j)}$$ - cost function to be minimized

<u>Iterations</u>:

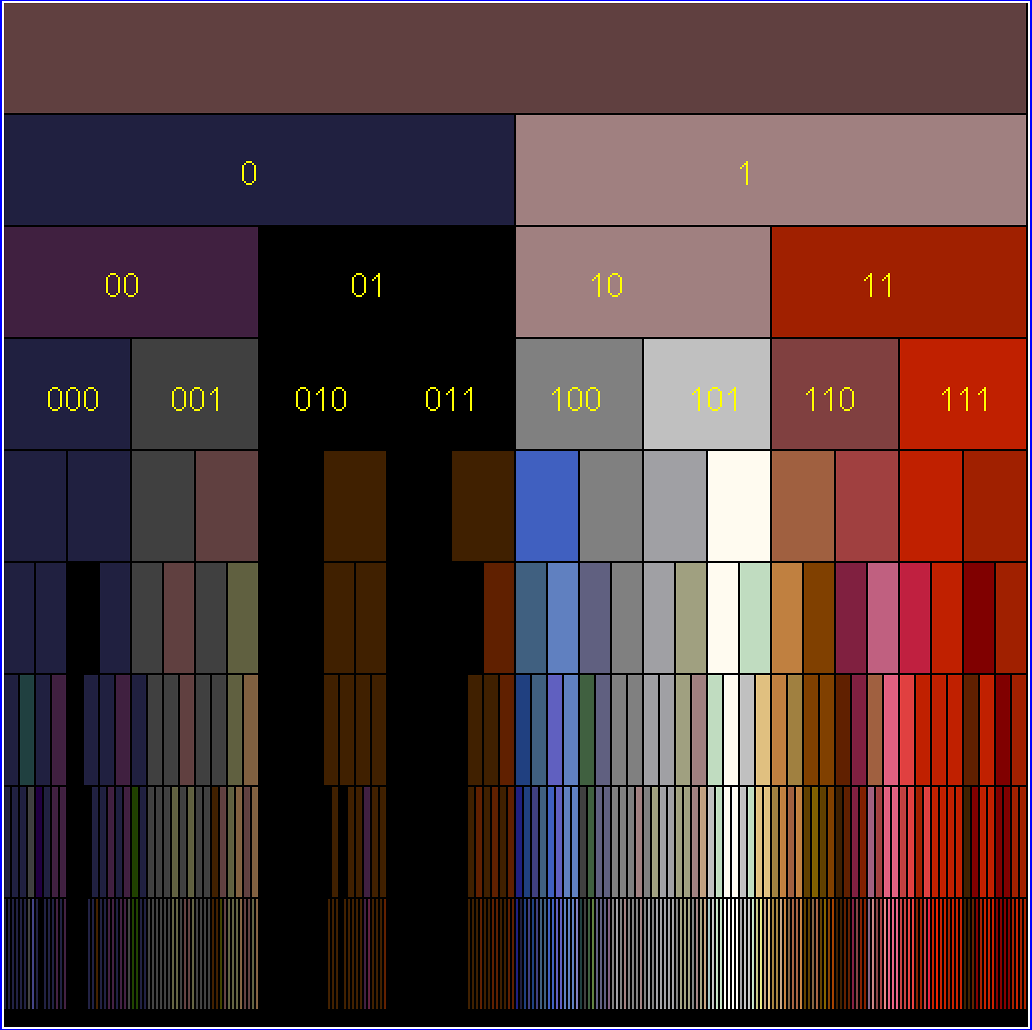
Steepest Descent based:

$$\nabla F(T)\Big|_{mn}=\frac{\partial F(T)}{\partial T_{mn}}=\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\left\{\left(\frac{1}{\tilde{d}(x_i,x_j)}-\frac{1}{d(x_i,x_j)}\right)\left[\sum_{k=1}^{k_2}T_{mk}\left(x_i^k-x_j^k\right)\right]\left(x_i^n-x_j^n\right)\right\}$$

$$T^{p+1}=T^p-\eta\nabla F$$

Bad results

Natural LBG Ordering



Natural LBG Ordering (cont'd)

<u>Improvement by Tree LBG:</u>

A node in the LBG tree uses only its father's data

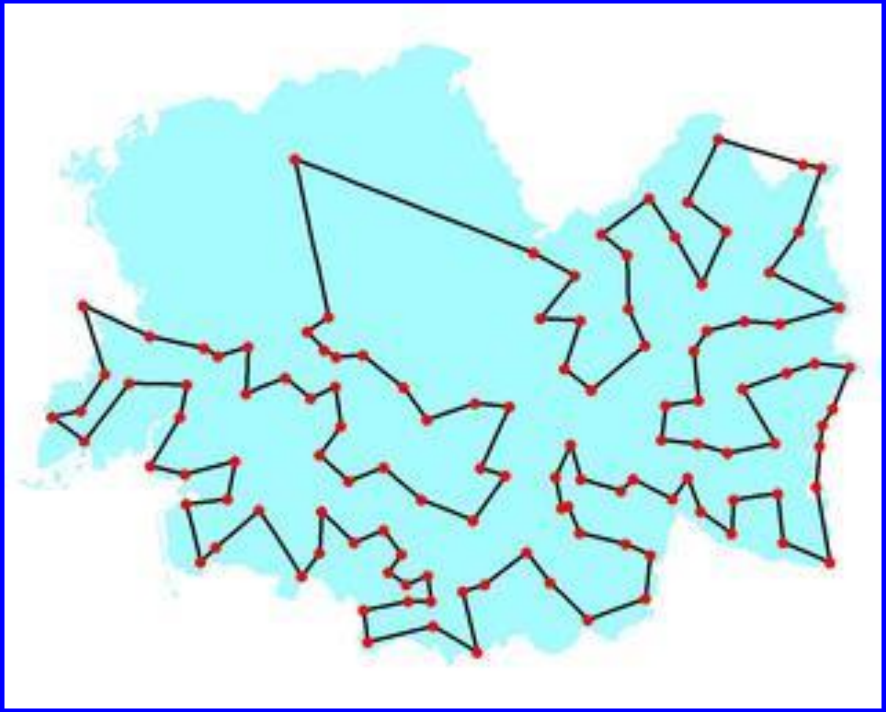
Advantages:

- Similar quantized image quality (for enough colors)
- Better spatial correlation in indexed image
- (Runs much faster)

Good results bad requires quantization by LBG

Traveling Salesman Problem (TSP)

Finding the shortest hamiltonian cycle (shortest closed tour passing through all data points)

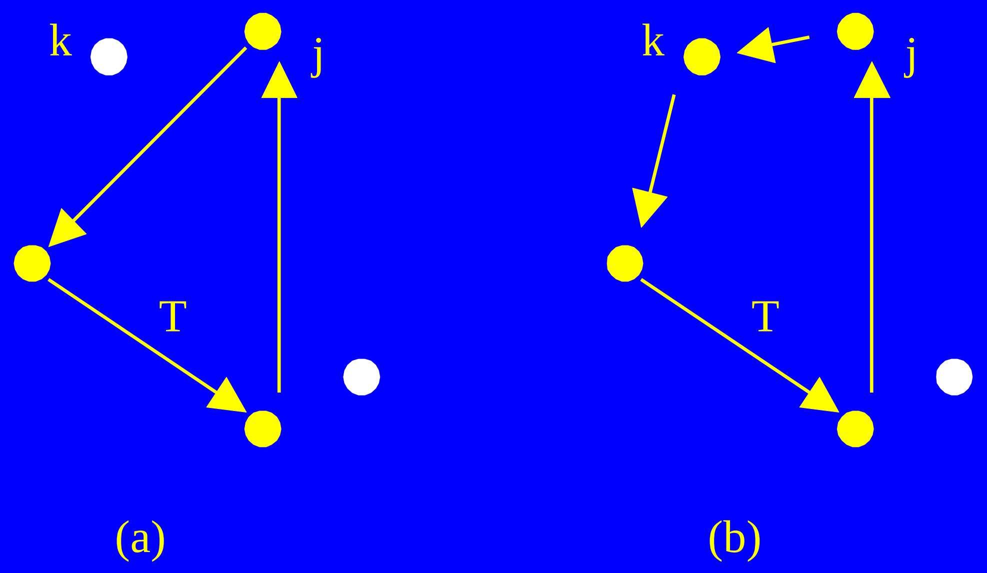


An NP-Complete problem with many good approximate solutions

TSP (cont'd)

By solving the TSP, the "Computer Wiring Problem" (shortest open tour) is solved.

<u>Farthest Insertion Algorithm (FIA)</u>:



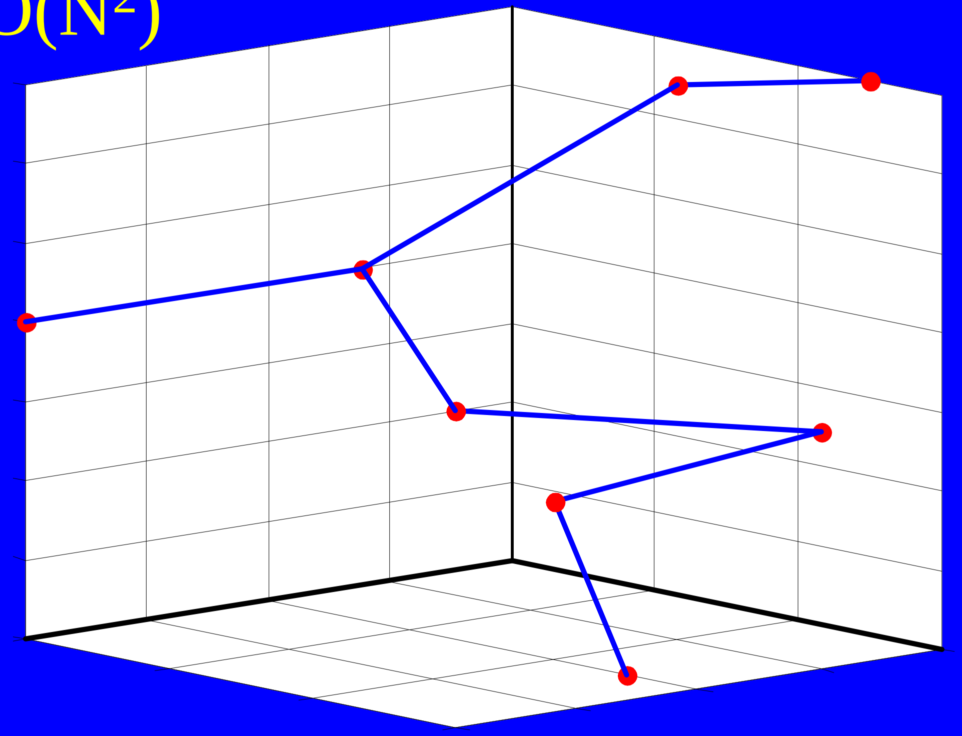
- Complexity of $O(N^3)$
- On average 5% longer than the optimal cycle

TSP (cont'd)

Minimal Spanning Tree (MST) bound:

$$2 \times length(MST) \geq length(TSP) \geq length(MST)$$

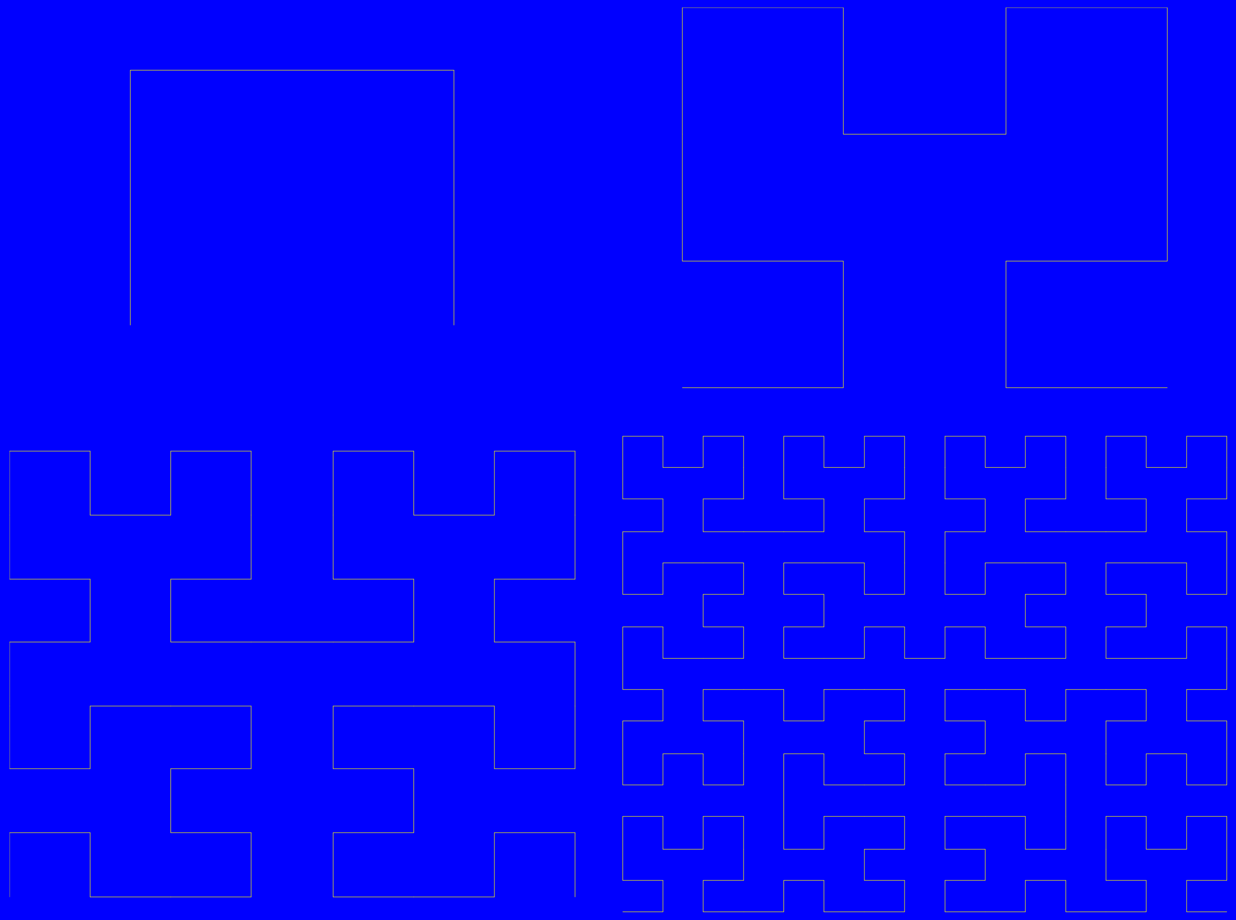
MST can be found in $O(N^2)$



Good results, but maybe bad trade-off between visual quality and compressibility

Hilbert Scan [Hilbert, 1891]

A Space Filling Curve with good locality properties



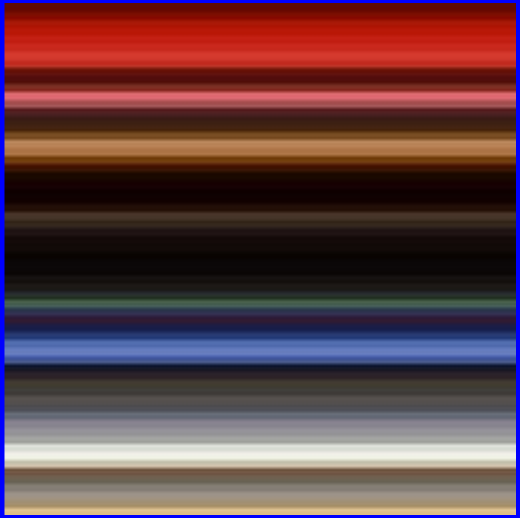
Hilbert Scan (cont'd)

The proposed method:

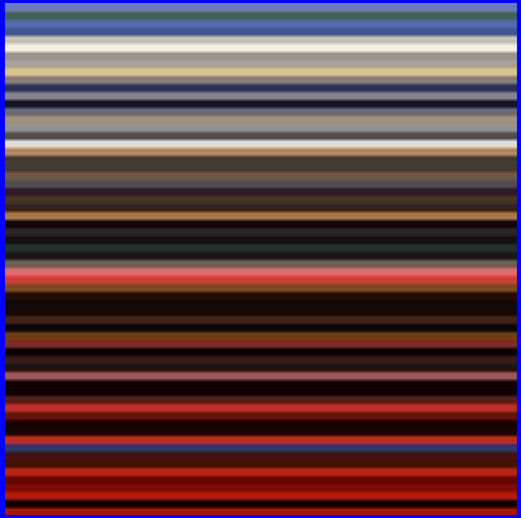
- Divide the 3D color space to cubes so that each color from the palette is in a different cube
- Build a 3D Hilbert scan with the required resolution
- The order in which the palette colors are scanned is the color ordering

Might give a better balance than the TSP between close indices -> similar colors (good visually) and similar colors -> close indices (better compression)

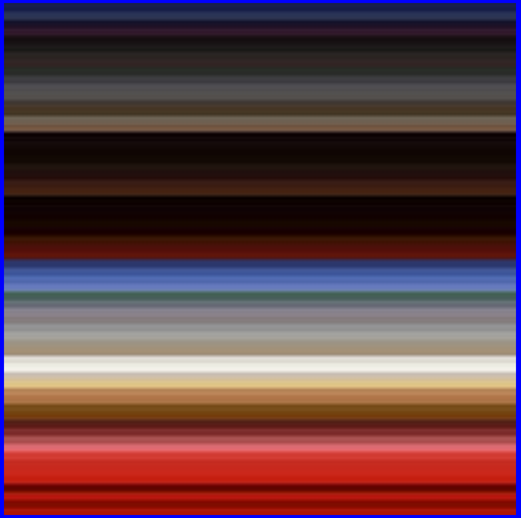
Color Ordering Results



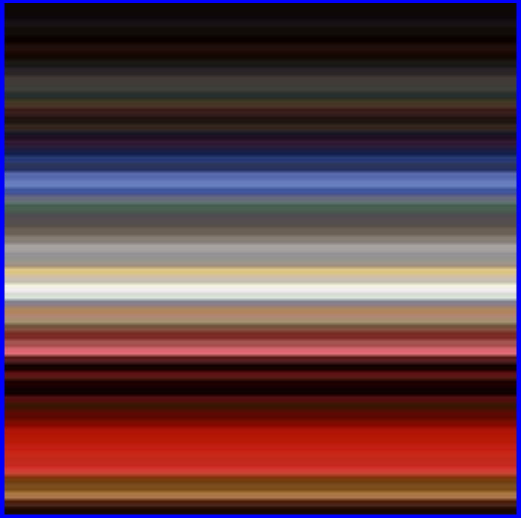
BSA



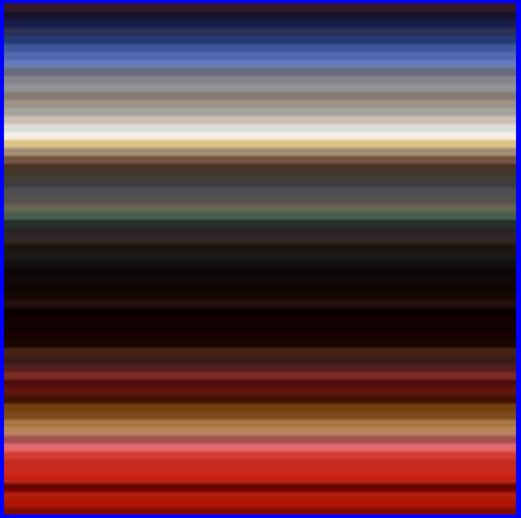
MDS



LBG



Hilbert



TSP

Lossless Compression of Natural Images

- LOCO uses a predictor and a context-based Golumb-Rice coding
- The coding assumes the predictor residuals have a Laplacian distribution (smooth image)
- A randomly color ordered indexed image is not smooth
- Color ordering will result in a smoother indexed image and better compression

Lossless Compression (cont'd)

	Y	Cb	Cr	Total	Quant.	Rand.	TSP	GIF
yarn	3.96	3.16	2.69	9.81	9.91	6.90	4.60	4.69
flower	3.88	2.54	2.29	8.71	8.41	5.62	3.53	4.05
monkey	5.81	4.81	4.74	15.36	15.61	8.34	6.77	7.72

Regular LOCO (Y, Cb, Cr, Total, Quant.)

Proposed Method (Rand., TSP)

Lossy Compression of Natural Images

- 256 colors
- TSP ordering
- q-factor - 75

<u>File sizes</u>:

This - 53K

JPEG - 44K

Lossy Compression (cont'd)

Why the results aren't good?

- With proper use of regular JPEG only 15-20% of the file size is due to chromatic components
- The indexed image has a wider dynamic range than the component images
- The color ordering didn't smooth the indexed image enough
- Color errors are very noticeable in smooth regions

Lossy Compression (cont’d)

Previous approach - local color ordering

Zaccarin et. al. (1991,1993,1994):

- Divide the image to regions (fixed division or according to color content)
- In each region give index according to luminance value
- DCT-based indexed image compression
- List of colors in each region as side information

Claims performance similar to JPEG above 1.25 bpp, below this rate has problems due to side information

Lossy Compression (cont'd)

Proposed approach - global color ordering

Allows deep compression (not hindered by side information)

To improve the global ordering:

- Reduced palette size (best improvement)
- Pre-quantization chromatic component smoothing
- Median filtering of indexed images
- Shape-Adaptive DCT (SA-DCT)

Lossy Compression (cont'd)

Reduced palette size:

Proposed method:

Quantized JPEG:

64 colors
q-factor - 75
size - 17K

64 colors
q-factor - 22
size - 17K

64 colors
q-factor - 75
size - 17.5K

64 colors
q-factor - 17
size - 17.5K

Lossy Compression (cont'd)

<u>Median Filtering</u>:

Proposed method:

64 colors
q-factor - 75
size - 14K

64 colors
q-factor - 75
size - 15.5K

Quantized JPEG:

64 colors
q-factor - 17
size - 14K

64 colors
q-factor - 14
size - 15.5K

Lossy Compression of Hyperspectral Images

<u>Why should the proposed method perform better for hyperspectral images?</u>

- Many color planes (not only “1½”)
- Performance is not measured visually
- Can work with a very small number of representative colors

Hyperspectral Images (cont'd)

The proposed method:

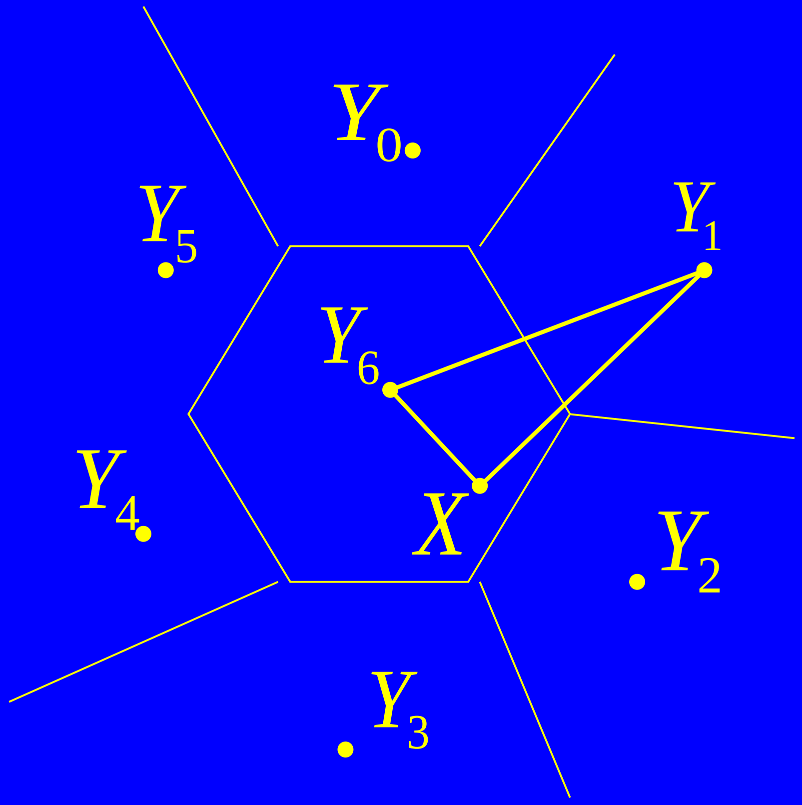
- Decide on number of color planes indexed together
- Decide on number of representative colors
- Quantize
- Compress the indexed images

Results:

- Promising partial results
- To be completed soon

The Index Assignment Problem

Index Assignment is the process of indexing the vectors in a codebook to reduce the distortion caused by transmission over a channel with errors



The Index Assignment Problem (cont'd)

The IA is a Quadratic Assignment problem,
therefore a "difficult" NP-Complete problem.

Known sub-optimal approaches include:

Binary Switching Algorithm (BSA) [Zeger et. al., 1990]

Simulated Annealing Algorithm (SAA) [Farvardin, 1990]

Linearity Increasing Swap Algorithm (LISA) [Knagenhjelm, 1996]

These are iterative approaches reaching a local minimum

The Index Assignment Problem (cont’d)

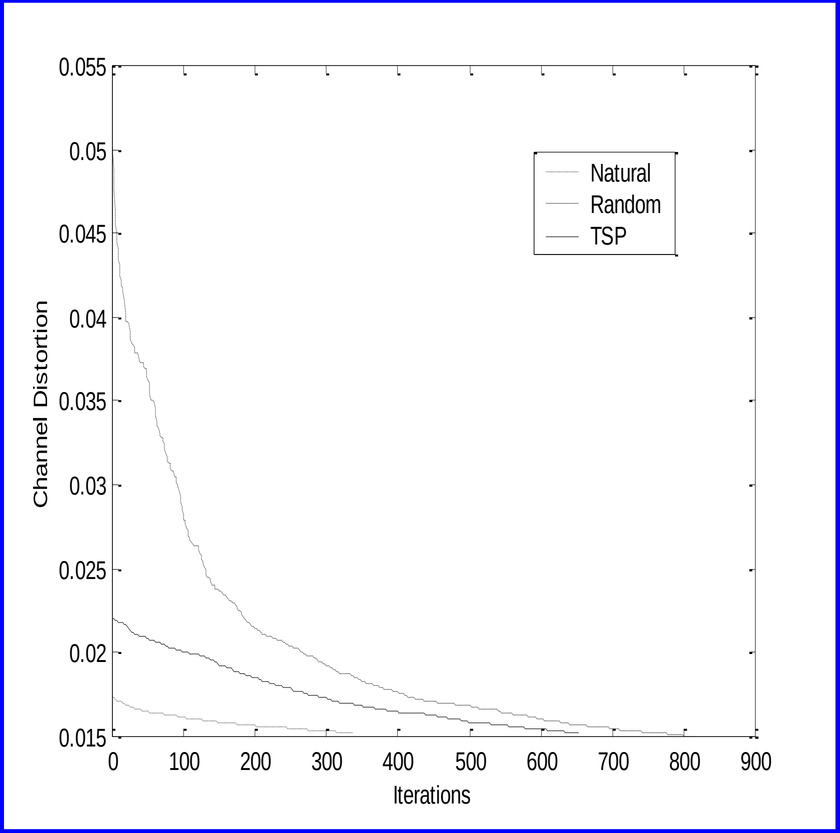
<u>The proposed method</u>:

- The natural LBG ordering is a good Index Assignment.
- If the LBG natural ordering is not given, use the FIA to generate an ordering
- The resulting TSP based ordering approximates the natural ordering of the LBG

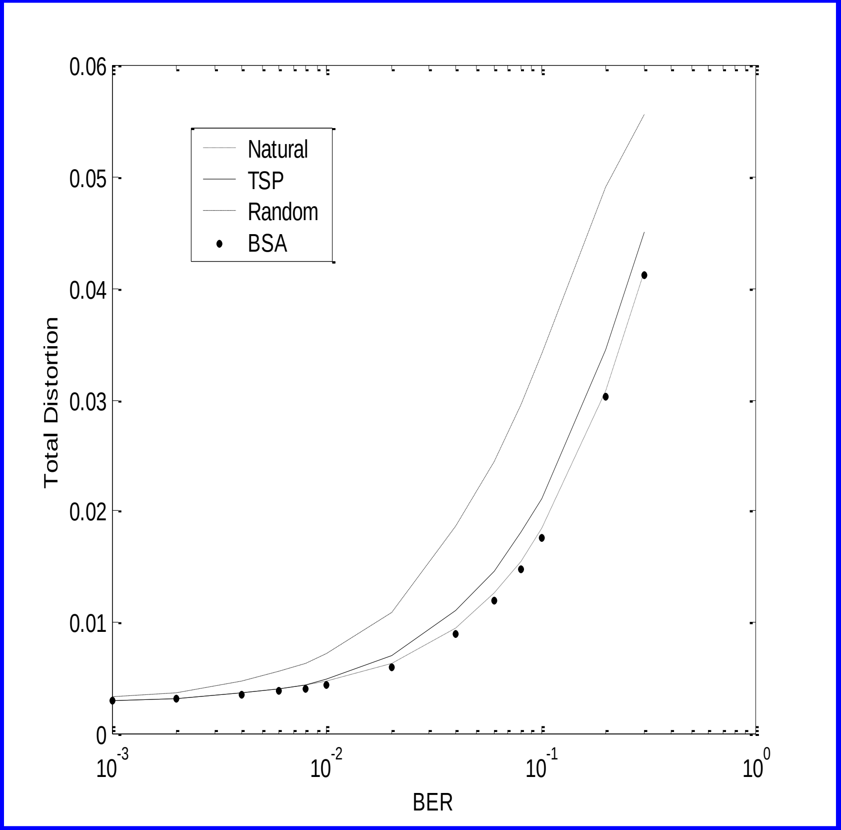
The Index Assignment Problem (cont'd)

Results:

Tested for codebooks generated for LSF vectors of speech



BSA results for the 3 orderings



Total distortion as a function of Bit Error Rate

Conclusions

- The proposed method is beneficial for lossless compression of natural indexed images
- The proposed method enables deep lossy compression with quantization at the sender
- The visual quality of the lossy approach is less than that of regular JPEG
- The proposed methods looks promising for hyperspectral image compression
- A good Index Assignment is given quickly and simply by the TSP based approach

Future Work

- Fine tune the LOCO to the proposed lossless compression method
- Improve the Hilbert scan based color ordering by selecting a scan instance compatible to the specific palette (for lossy compression)
- Test the quality of the hyperspectral image compression by applying a classification task