# Wavelet and image compression

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22 Novembre 2012

# Plan

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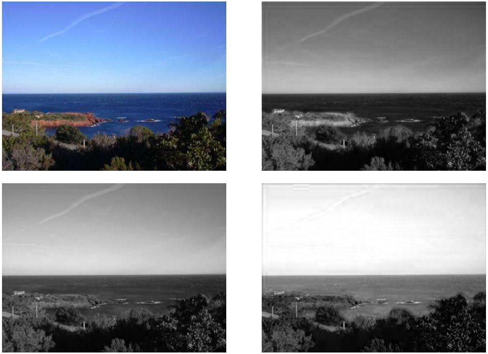
# Digital images representation

- Image as an $N \times M$ matrix of "pixels"
- Color images: three channels i.e. components
- Each channel (red, green, blue) is in turns an $N \times M$ matrix



# Digital image representation
## Color images: YCbCr format

- Coordinates transformation: $[R, V, B] \rightarrow [Y, C_b, C_r]$
- Luminance $Y$ and chrominance $C_b, C_r$

# Why compression

- Photos : 5 Megapixel
- Three channels
- One byte per channel
- 15 MB per photo
- Video SD, 720$\times$ 576 pixel, 25 images per second
  - Rate: 125 Mbps
  - 2 hours: more than 100 GB
- Video HD, 1920$\times$ 1080 pixel, 50 images per second
  - Rate: 1250 Mbps
  - 2 hours: more than 1 TB

# Compression and redundancy

- Statistical redundancy
  - Images are homogeneous
  - Statistical dependency among pixels
- Psycho-visual redundancy
  - Spatial frequency sensitivity
  - Masking effects
  - Contours importance
  - Other limits of the HVS
- Transform coding: we pass from $NM$ luminance values (all equally important) to only $n \ll NM$ significant transform coefficients

# Compression algorithms

- *Lossless* algorithms
  - Perfect reconstruction
  - Based on statistical redundancy
  - Low compression ratio
- *Lossy* algorithms
  - Decoded image $\neq$ original image
  - Based on transform and quantization
  - “Visually lossless”
  - High compression ration

# Wavelets and images : Motivations

- Image model : *trends* + *anomalies*

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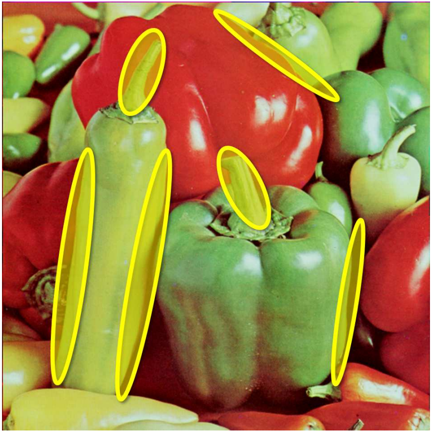


# Wavelets and images : Motivations

- Image model : *trends* + *anomalies*

# Wavelets and images : Motivations

- *Anomalies* :
  - Abrupt variations of the signal
  - High frequency contributions
  - Objects' contours
  - Good spatial resolution
  - Rough frequency resolution
- *Trends* :
  - Slow variations of the signal
  - Low frequency contributions
  - Objects' texture
  - Rough spatial resolution
  - Good frequency resolution

# Wavelets and images : Motivations

## Time-frequency boxes of basis signals

Time analysis:
$\theta_\gamma(t) = \delta(t - t_0)$
Frequency analysis:
$\theta_\gamma(t) = e^{2i\pi f_0 t}$
Short Time Fourier Transform (STFT):

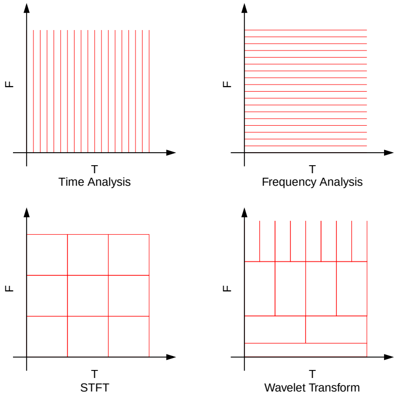
$$\theta_\gamma(t) = g(t - t_0)e^{2i\pi f_0 t}$$

$\sigma_t, \sigma_\xi$ independent from $\gamma$

Wavelet Transform:

$$\theta_\gamma(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

$$\sigma_{t(a,b)} = a\sigma_{t,(1,0)} \quad \sigma_{\xi(a,b)} = a^{-1}\sigma_{\xi,(1,0)}$$



# Wavelets and images : Motivations

Signal model: an image row

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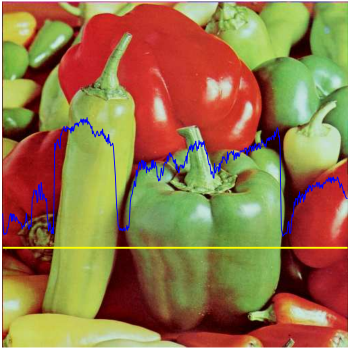
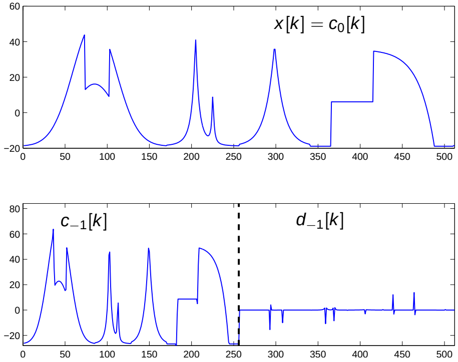


# Wavelets and Multiple resolution analysis

- Approximation: low resolution version
- “Details”: zeros when the signal is polynomial



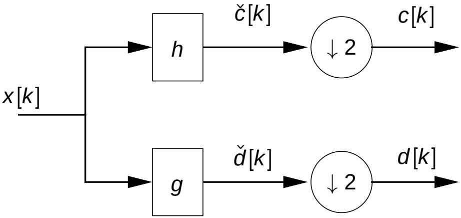
# Plan

1. Introduction

2. Discrete Wavelet Transform
   - Filter banks
   - Multiresolution analysis

3. Images compression
   - EZW
   - JPEG 2000

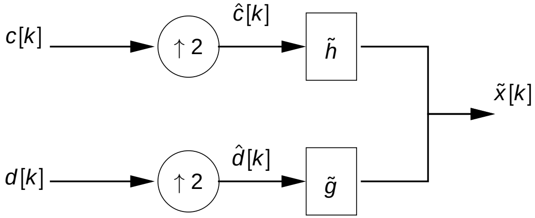
# 1D filter banks
## Decomposition




Analysis filter bank

$2 \downarrow$ : decimation : $c[k] = \check{c}[2k]$

# Reconstruction




Synthesis filter bank

$2\uparrow$: interpolation operator, doubles the sample number

$$\hat{c}[k] = \begin{cases} c[k/2] & \text{if } k \text{ is even} \\ 0 & \text{if } k \text{ is odd} \end{cases}$$

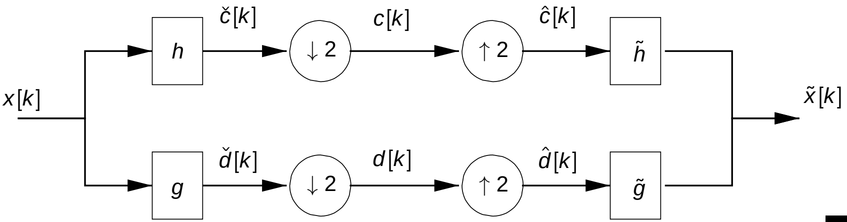
# Filter properties

- Perfect reconstruction (PR)
- FIR
- Orthogonality
- Vanishing moments
- Symmetry

# Perfect reconstruction conditions

We want PR after synthesis and analysis filter banks :
$\forall k \in \mathbb{Z}$,

$$\widetilde{x}_k = x_{k+\ell} \Longleftrightarrow \widetilde{X}(z) = z^{-\ell} X(z)$$



# Z-domain relationships

filter $$\check{C}(z) = \sum_{n=-\infty}^{\infty} \check{c}_n z^{-n} = H(z)X(z)$$

decimation $$C(z) = \frac{1}{2}\left[\check{C}\left(z^{1/2}\right) + \check{C}\left(-z^{1/2}\right)\right]$$

interpolation $$\hat{C}(z) = C\left(z^2\right)$$

output $$\widetilde{X}(z) = \widetilde{H}(z)C\left(z^2\right) + \widetilde{G}(z)D\left(z^2\right)$$

$$\widetilde{X}(z) = \frac{1}{2}\left[\widetilde{H}(z)H(z) + \widetilde{G}(z)G(z)\right]X(z) + \frac{1}{2}\left[\widetilde{H}(z)H(-z) + \widetilde{G}(z)G(-z)\right]X(-z)$$

# PR conditions in $Z$

$\forall k \in \mathbb{Z}$,

$$\widetilde{x}_k = x_{k+\ell} \Longleftrightarrow \widetilde{X}(z) = z^{-\ell} X(z)$$

$$\Updownarrow$$

$$\widetilde{H}(z)H(z) + \widetilde{G}(z)G(z) = 2z^{-\ell} \qquad \text{Non distortion}$$

$$\widetilde{H}(z)H(-z) + \widetilde{G}(z)G(-z) = 0 \qquad \text{Non aliasing}$$

# Perfect reconstruction conditions

## Matrix form

For simplicity, we ignore the delay, $\ell = 0$

If the analysis filter bank is given, the synthesis one is determined by:

$$\begin{bmatrix} H(z) & G(z) \\ H(-z) & G(-z) \end{bmatrix} \cdot \begin{bmatrix} \widetilde{H}(z) \\ \widetilde{G}(z) \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

We assume that the *modulation matrix* is invertible.

# Perfect reconstruction conditions
## Synthesis filter bank

Modulation matrix determinant :

$$\Delta(z) = H(z)G(-z) - G(z)H(-z)$$

$$\widetilde{H}(z) = \frac{2}{\Delta(z)}G(-z)$$

$$\widetilde{G}(z) = -\frac{2}{\Delta(z)}H(-z)$$

# Perfect reconstruction with FIR filters

Finite impulse response filters:
It can be shown that in this case the PR condition is equivalent to the altering signs condition. Example:

$$h(k) = \boxed{a}\boxed{b}\boxed{c} \qquad \widetilde{h}(k) = \boxed{p}\boxed{-q}\boxed{r}\boxed{-s}\boxed{t}$$

$$g(k) = \boxed{p}\boxed{q}\boxed{r}\boxed{s}\boxed{t} \qquad \widetilde{g}(k) = \boxed{-a}\boxed{b}\boxed{-c}$$

# Orthogonality

Orthogonality assures energy conservation:

$$\sum_{k=-\infty}^{\infty} (x_k)^2 = \sum_{k=-\infty}^{\infty} (c_k)^2 + \sum_{k=-\infty}^{\infty} (d_k)^2$$

$\Rightarrow$ reconstruction error = quantization error on DWT coefficients
For non orthogonal filters, the reconstruction errors is a weighted sum of the quantization errors on the DWT subbands, with suitable weights $\omega_i$

# Vanishing moments

- Vanishing moments (VM) represent filter ability to reproduce polynomials: a filter with $p$ VM can represent polynomials with degree $< p$
- The High-pass filter will not respond to a polynomial input with degree $< p$
- In this case all the signal information is preserved in the approximation signal (half the samples)
- A filter with $p$ VM has at least $2p$ taps

# Haar filter

$$h(k) = \boxed{1}\,\boxed{1} \qquad \tilde{h}(k) = \boxed{1}\,\boxed{1}$$

$$g(k) = \boxed{1}\,\boxed{-1} \qquad \tilde{g}(k) = \boxed{-1}\,\boxed{1}$$

- Symmetric
- Orthogonal
- VM = 1
  - Only capable to represent piecewise constant signals

# Orthogonality and biorthogonalty

## Perfect reconstruction for finite duration signals

- Convolution involves coefficient expansion
- Solution: circular convolution
  - Circular convolution allows to reconstruct an $N$-samples signal with $N$ wavelet coefficients
  - The periodization generates borders discontinuities, i.e. spurious high frequencies coefficients that demand a lot of coding resources
- Solution: Symmetric periodization
  - No discontinuities
  - Does it double the coefficient number?
  - No, if the filter is **symmetric**!

Bad news: the only orthogonal symmetric FIR filter is Haar!

# Biorthogonal filters

## Cohen-Daubechies-Fauveau filters

With biorthogonal (i.e. PR) filters, if $h$ has $p$ VM and $\widetilde{h}$ has $\widetilde{p}$ VM, the filter has at least $p + \widetilde{p} - 1$ taps.

The CDF filters have the following properties:

- They are symmetric (linear phase)
- They maximize the VM for a given filter length
- They are close to orthogonality (weights $\omega_i$ are close to one)

They are by far the most popular in image compression

# 9/7 biorthogonal filters

Filter coefficients:

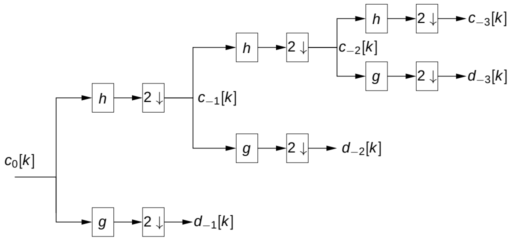
| $n$ | 0 | $\pm 1$ | $\pm 2$ | $\pm 3$ | $\pm 4$ |
|---|---|---|---|---|---|
| $h[l]$ | 0.852699 | 0.377403 | $-0.110624$ | $-0.023849$ | 0.037828 |
| $\widetilde{h}[l]$ | 0.788486 | 0.418092 | $-0.040689$ | $-0.064539$ | |

Impulse response of low-pass filters

For high pass filters, we have (altering sign condition):

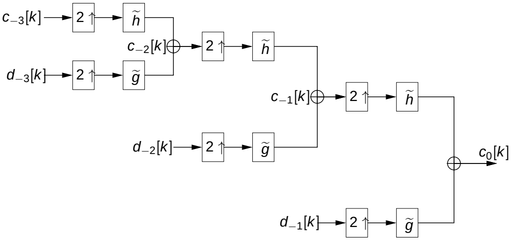
$$g[l] = (-1)^{l+1}\,\widetilde{h}\,[l-1] \qquad \text{and} \widetilde{g}[l] = (-1)^{l-1}\,h\,[l+1]\,.$$

# 1D Multiresolution analysis
## Decomposition




Three level wavelet decomposition structure

# Reconstruction

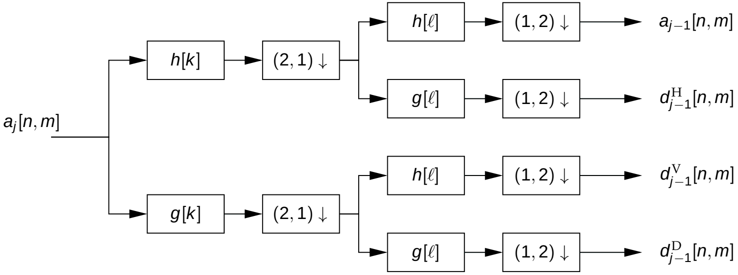



Reconstruction from wavelet coefficients

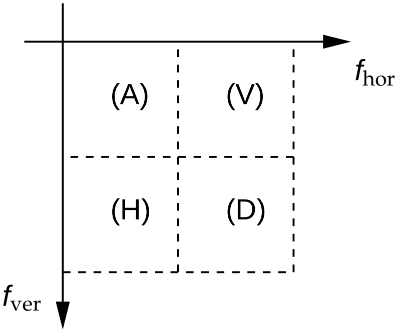
# 2D AMR

## 2D Filter banks for separable transform

### One decomposition level

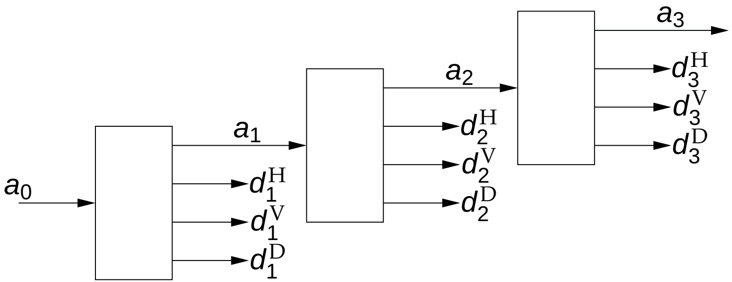


# 2D-DWT subbands: orientations



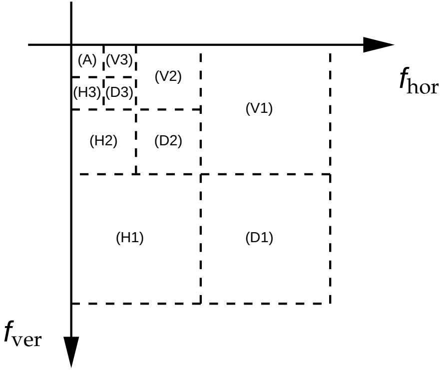

(A), (H), (V) and (D) respectively correspond to approximation coefficients, horizontal, vertical and diagonal detail coefficients.

# 2D AMR: multiple levels

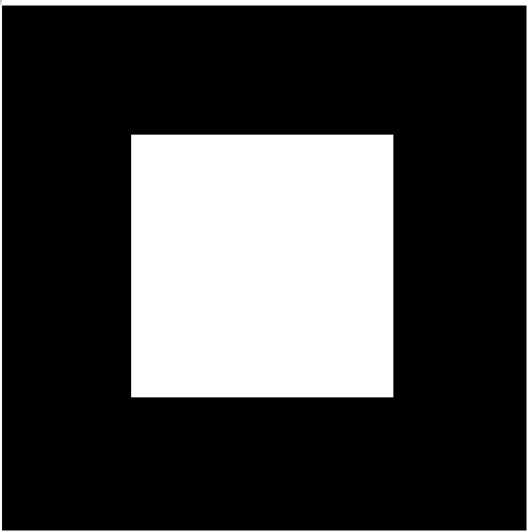



Three levels of separable 2D-AMR.

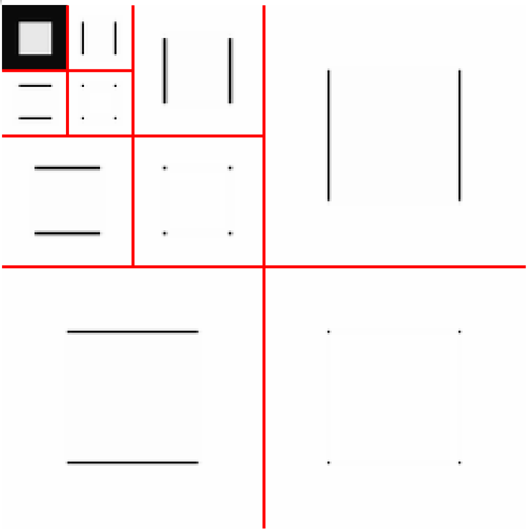
# 2D-DWT subbands: orientations



# Example

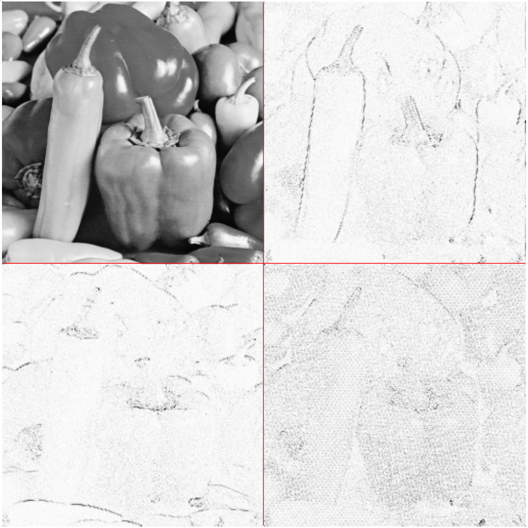


# Example

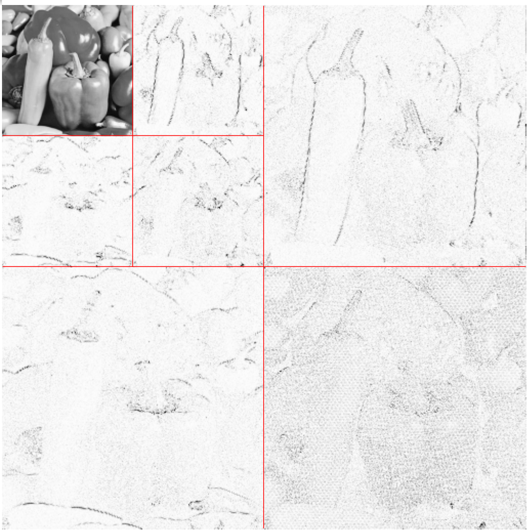


# Example

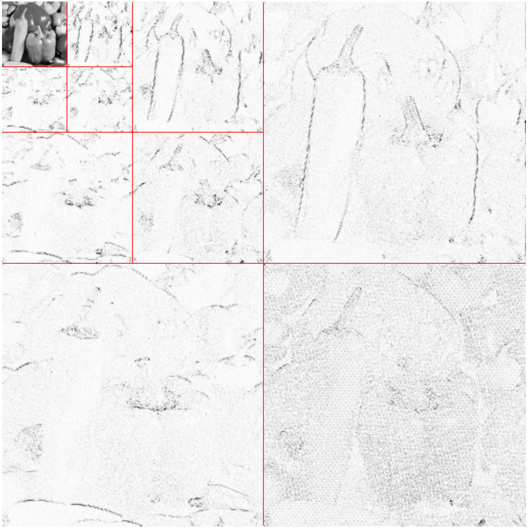
# Example



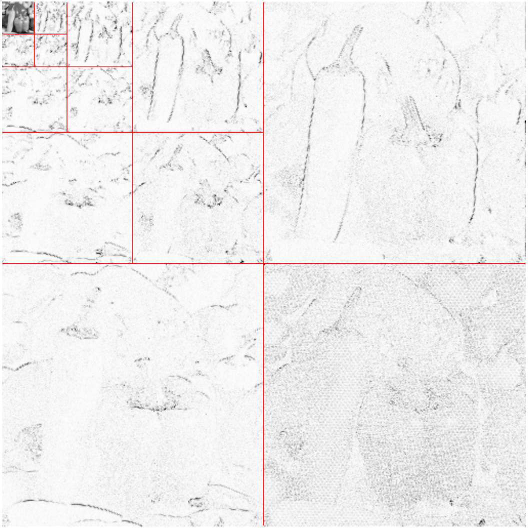
# Example



# Example



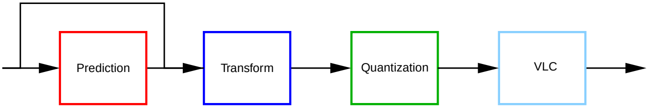
# Example



# Plan

# Basic tools for compression

- Transform
  - It concentrates information in a few coefficients
- Prediction
  - Alternative (and sometimes additional) method for information concentration
- Quantization
  - Rate reduction: rough representation of less important coefficients
- Lossless coding, or variable length coding (VLC)
  - Residual redundancy reduction



# Performance criteria
## Rate

Compression ratio:

- $T = \frac{B_{\text{in}}}{B_{\text{out}}} = \frac{R_{\text{in}}}{R_{\text{out}}}$

Coding Rate

- Image: $R = \frac{B_{\text{out}}}{NM}$ [bpp]
- Video, sound: $R = \frac{B_{\text{out}}}{T}$ [bps]

# Performance criteria

## Quality and distortion

Rate alone is not sufficient for evaluate a lossy coding algorithm. We need to assess quality or distortion for the reconstructed image

- The **Objective criteria** are mathematical functions of
  - $f_{n,m}$ : the original image; and
  - $\widetilde{f}_{n,m}$ : the reconstructed image
- Non-perceptual objective criteria: they do not take into account the characteristics of the Human Visual System (HVS)
- Perceptual objective criteria: try to model the HVS

# Performance criteria

## Non-perceptual objective criteria

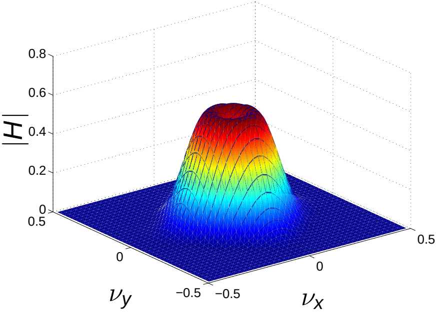
- Error image: $\mathcal{E}(f,\widetilde{f}) = f - \widetilde{f}$
- **Mean Square Error** (MSE) $\mathcal{D}$:

$$\mathcal{D}(f,\widetilde{f}) = \frac{1}{N\,M}\left\|\mathcal{E}\right\|^2 = \frac{1}{N\,M}\sum_{n=1}^{N}\sum_{m=1}^{M}\mathcal{E}_{n,m}^2$$

- **Peak Signal-to-Noise Ratio**:
$\mathrm{PSNR}(f,\widetilde{f}) = 10\,\log_{10}\left(\frac{255^2}{\mathcal{D}(f,\widetilde{f})}\right)$
- Simple, derivable, related to the $\mathcal{L}^2$ norm

# Performance criteria
## Perceptual objective criteria

**Weighted PSNR**: Given a frequency weighting function (a linear filter) $h$:




$$\mathrm{WPSNR}(f,\widetilde{f}) = 10\log_{10}\left(\frac{255^2}{\mathcal{D}_{\mathrm{W}}(f,\widetilde{f})}\right)$$ where

$$\mathcal{D}_{\mathrm{W}}(f,\widetilde{f}) = \frac{1}{NM}\left\|h * \mathcal{E}\right\|^2$$

# Performance criteria
## Perceptual objective criteria

**Structural Similarity Index** (SSIM Index) between two blocks $x$ et $y$:

$$\mathrm{SSIM}(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \qquad \text{Luminance}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \qquad \text{Contrast}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \qquad \text{Structure}$$

for simplicity, $\alpha = \beta = \gamma = 1$, $C_3 = C_2/2$

$$\mathrm{SSIM} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

Le SSIM between two images is the average block SSIM

# Quality evaluation: Example

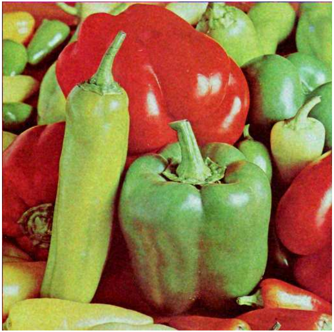
Image Originale, 24 bpp

# Quality evaluation: Example

White noise $\sigma = 4$

Image Originale, 24 bpp

Erreur dispersée, MSE = 16.00



# Quality evaluation: Example

Moise concentrated on $100 \times 100$ pixels

Image Originale, 24 bpp

Erreur concentrée, MSE = 16.00

# Quality evaluation: Example

Bruit concentrated on contours (estimated by the Sobel filter)

Contours de l'image

Erreur concentrée sur les contours, MSE = 16.00

# Quality evaluation: Example

Noise on high spatial frequencies

Image Originale, 24 bpp

Erreur en frequence, MSE = 16.00

# Quality evaluation: Example

## Chrominance subsampling

Image Originale, 24 bpp

Sous−echantillonement en couleur, MSE = 21.27

# Performance criteria
## Quality and distortion

- The **subjective criteria** are based on human observation of images
  - Need for result statistical analysis
  - Time-consuming, difficult, expensive process
- In conclusion, the non perceptual objective criteria are the most used in practice:
  - They are simple to implement and interpret
  - They are related to a geometric norm
  - They allow analytical optimization
  - Relationship with subjective quality is sometimes questioned

# Performance criteria
## Complexity, delay and robustness

- An algorithm complexity could be limited by:
  - Application related constraints (i.e. real-time operation)
  - Hardware limitations
  - Economic cost
- The delay, usually measured at the encoder side
  - is related to the complexity
  - Influenced by the coding order
- Robustness: algorithm sensitivity to alterations to the encoded data

# Performance criteria
## Summary

Contrasting needs:

$\Uparrow$ Quality
$\Uparrow$ Robustness

$\Downarrow$ Rate
$\Downarrow$ Complexity
$\Downarrow$ Delay

# Compression with DWT

- Methods based on inter-scale dependencies:
  - EZW (Embedded Zerotrees of Wavelet coefficients),
  - SPIHT (Set Partitioning in Hierarchical Trees)
  - Tree-based representation of dependencies
  - Advantages: good exploitation of inter-scale dependencies, low complexity
  - Disadvantage: no resolution scalability
- Methods not based on inter-scale dependencies
  - Explicit bit-rate allocation among subbands
  - Entropy coding of coefficients
  - Advantages: Good exploitation of intra-scale dependencies, random access, resolution scalability
  - Disadvantage: no exploitation of inter-scale dependencies

# Embedded Zerotrees of Wavelet coefficients

Main characteristics

- Quality scalability (i.e. progressive representation)
- Lossy-to-lossless coding
- Small complexity
- Rate-distortion performance much better than JPEG **above all at small rates**

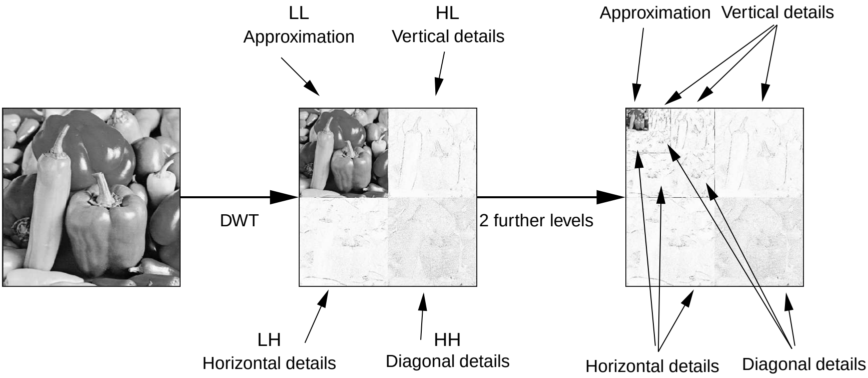
# Progressive representation of DWT coefficients

- Each new coding bit must convey the maximum of information

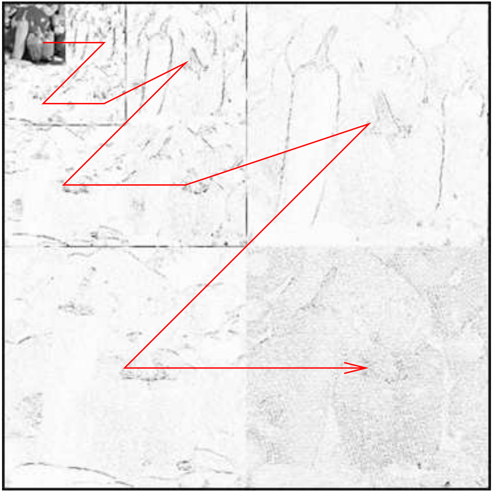
$$\Updownarrow$$

- Each new coding bit must reduce as much as possible distortion
- We first send the largest coefficients
- Problem: localization overhead

# Example: an image and its wavelet coefficients



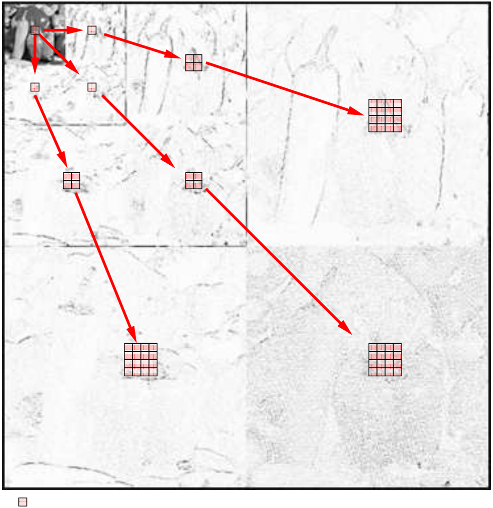
# Progressive representation: subband order



# EZW Algorithm

- The subband scan order alone is not enough to assure that largest coefficients are sent first
- We need to localize the largest coefficients
- Without having to send explicit localization information
- Idea: to exploit the inter-band correlation to predict the position of non-significant coefficients
- If the prediction is correct we save many coding bits (for all the predicted coefficients)

# Zero-tree of wavelet coefficients



# EZW idea

- **Auto-similarity** : When a coefficient is small (below a threshold) it is probable that its descendants are small as well
- In this case we use a single coding symbol to represent the coefficient and all its descendants. If $c$ and all its descendants are smaller than the threshold, $c$ is called a zero-tree root
- With just one symbol, (ZT) we code $(1 + 4 + 4^2 + \ldots + 4^{N-n})$ coefficients
- The localization information is implicit in the significance information

# EZW algorithm

1. $k = 0$
2. $n = \lfloor \log_2 (|c|_{\max}) \rfloor$
3. $T_k = 2^n$
4. while (rate < available rate)
   - Dominant pass
   - Refining pass
5. $T_{k+1} \leftarrow T_k/2$
6. $k \leftarrow k + 1$ end

# Dominant pass

- For each coefficient $c$ (in the scan order)
- If $|c| \geq T_n$, the coefficient is significant
  - If $c > 0$ we encode SP (Significant Positive)
  - If $c < 0$ we encode SN (Significant Negative)
- If $|c| < T_n$, we compare all its descendants with the threshold
  - If no descendant is significant, $c$ is coded as a zero-tree root (ZT)
  - Otherwise the coefficient is coded as Isolated Zero (IZ)

# Refining pass

- We encode a further bit for all significant coefficients
- This is equivalent to halve the quantization step

# Iteration and termination

- The $k$-th dominant pass allows to encode the $k$-th bit-plane
- A significant coefficient $c$ is such that $2^k < |c| < 2^{k+1}$
- For the next step we halve the threshold: it is equivalent to pass to the next bitplane
- Algorithm stops when
  - the bit budget is exhausted; or when
  - all the bitplanes have been coded

# EZW Algorithm: summary

- Bitplane coding: at the $k$-th pass, we encode the bitplane $\log_2 T_k$
- Progressive coding: each new bitplane allows refining the coefficients quantization
- Lossless coding of significance symbols
- Lossless-to-lossy coding: When an integer transform is used, and all the bitplanes are coded, the original image can be restored with zero distortion

# JPEG2000

- JPEG2000 aims at challenges unresolved by previous standards:
- Low bit-rate coding: JPEG has low quality for $R < 0.25$ bpp
- Synthetic images compression
- Random access to image parts
- Quality and resolution scalability

# New functionalities

- Region-of-interest (ROI) coding
- Quality and resolution scalability
- Tiling
- Exact coding rate
- Lossy-to-lossless coding

# Algorithm

JPEG2000 is made up of two *tiers*

- First tier
  - DWT and quantization
  - Lossless coding of codeblocks
- Second tier
  - **EBCOT**: embedded block coding with optimized truncation
  - Scalability (quality, resolution) and ROI management

# Quantization in JPEG2000

- DWT coefficients are encoded with a very fine quantization step
- For the lossless coding case, DWT coefficients are integers, and they are not quantified
- In summary, it is not in the quantization step that the really lossy operations are performed
- The lossy coding is performed by the bitstream truncation of Tier 2

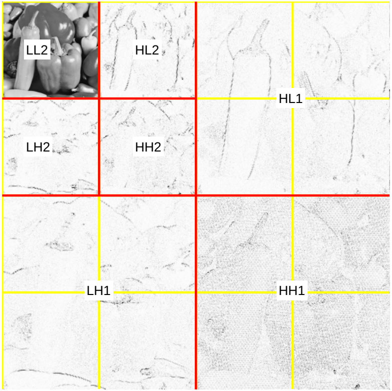
# EBCOT

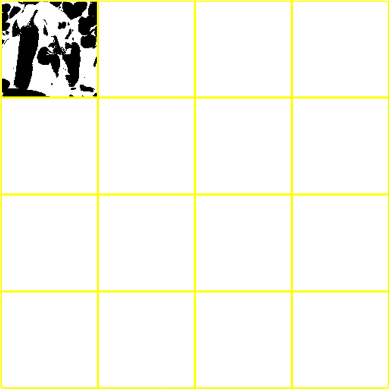
*Embedded Block Coding with Optimized Truncation*

- Each subband is split in equally sized blocks of coefficients, called codeblocks
- The codeblocks are losslessly and independently coded with an arithmetic coder
- We generate as much bitstreams as codeblocks in the image

# Bitplane coding

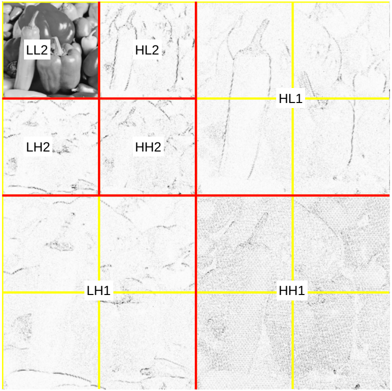
## Most significant bitplane

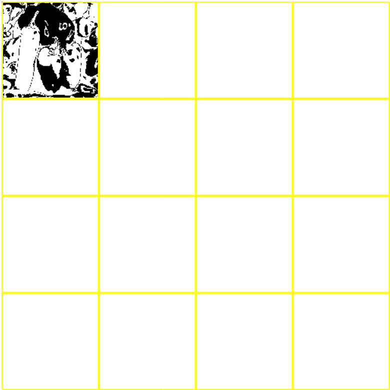


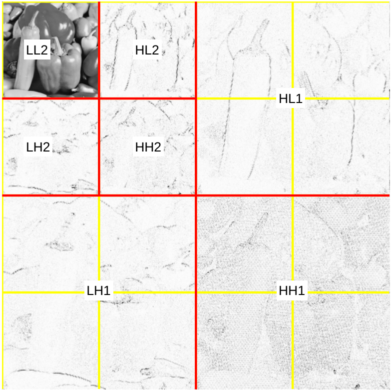
# Bitplane coding

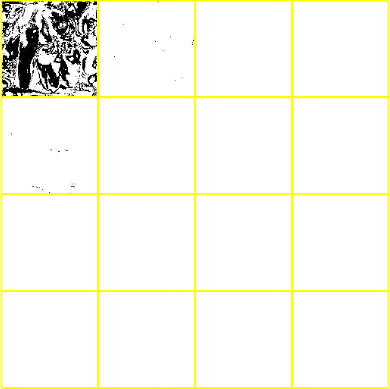
## Second bitplane



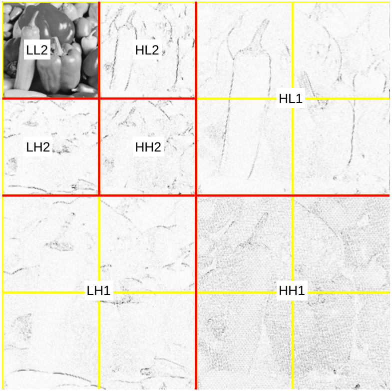
# Bitplane coding
## Third bitplane

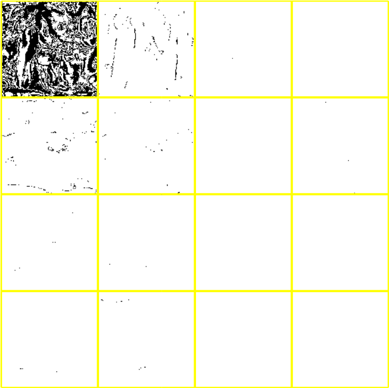


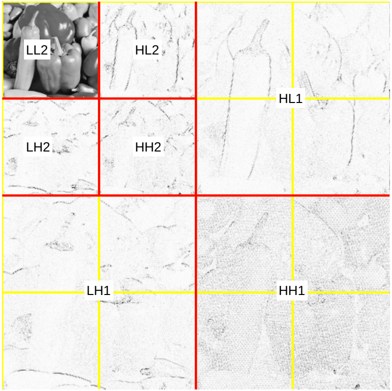
# Bitplane coding

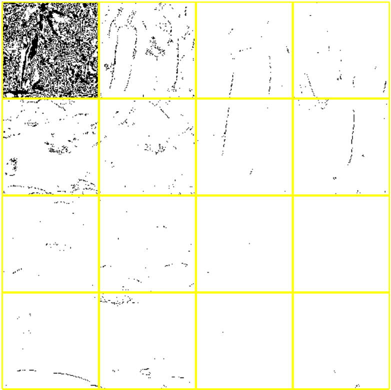
## Fourth bitplane



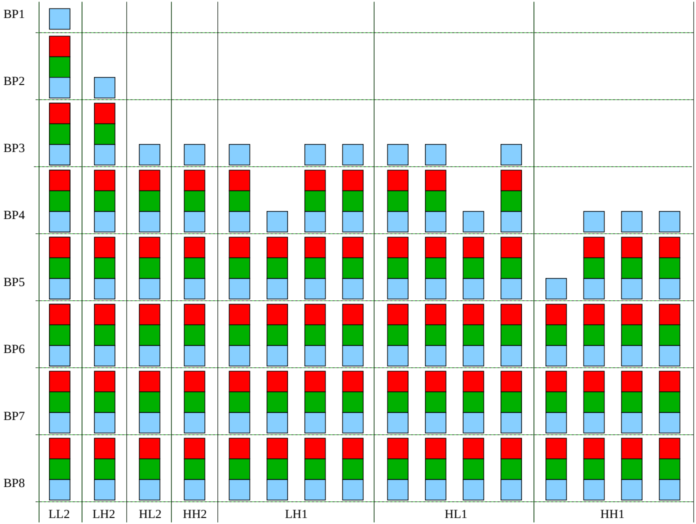



# Bitplane coding
## Fifth bitplane



# Example of bitstreams associated to codeblocks



# EBCOT
## Optimization

- If we keep all the bitstreams of all the codeblocks, we end up with a huge bitrate
- We have to truncate the bitstream to attain the target bit-rate
- Problem: how to truncate the bitstreams with a minimum resulting distortion?

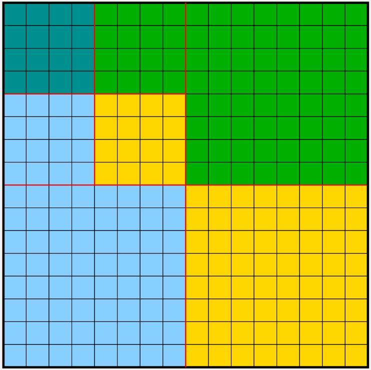
$$\min \sum_i D_i$$

$$\sum_i R_i \leq R_{\text{tot}}$$

- Solution : Lagrange multiplier

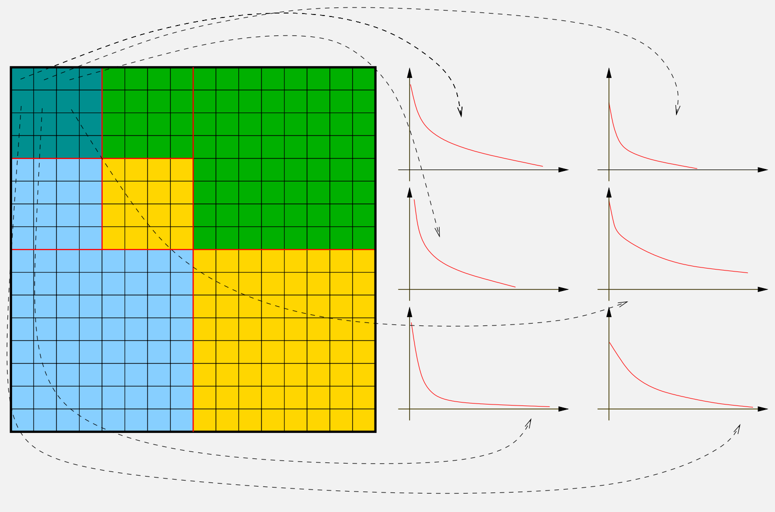
$$J = \sum_i D_i + \lambda \left( \sum_i R_i - R \right)$$

# EBCOT
## Rate-distortion curve per each codeblock



# EBCOT

## Rate-distortion curve per each codeblock



# EBCOT

## Embedded block coding with optimized truncation

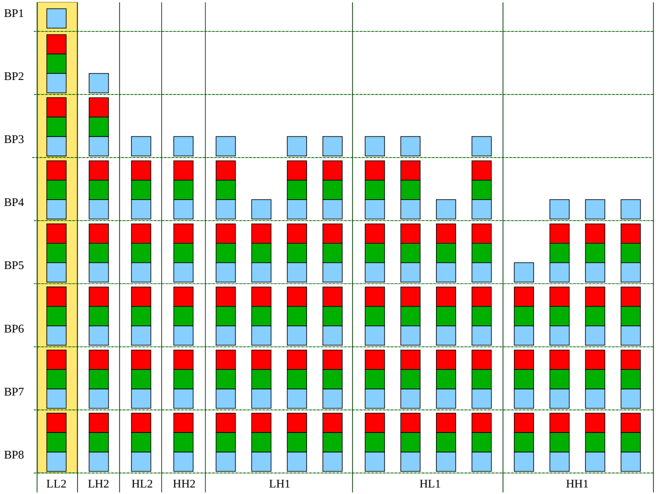
- Optimal truncation point:

$$\frac{\partial D_i}{\partial R_i} = -\lambda$$

- The value of the Lagrange multiplier can be find by an iterative algorithm.
- We can have several truncations for several target rates (quality scalability)

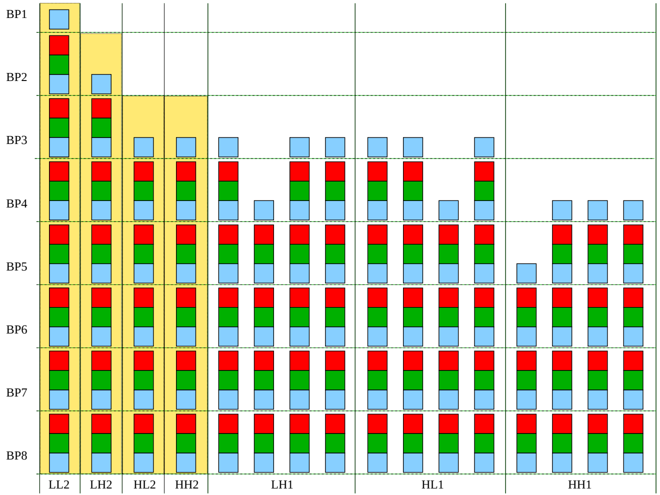
# Example of bit-rate allocation with EBCOT

## Allocation for maximal quality and minimal resolution



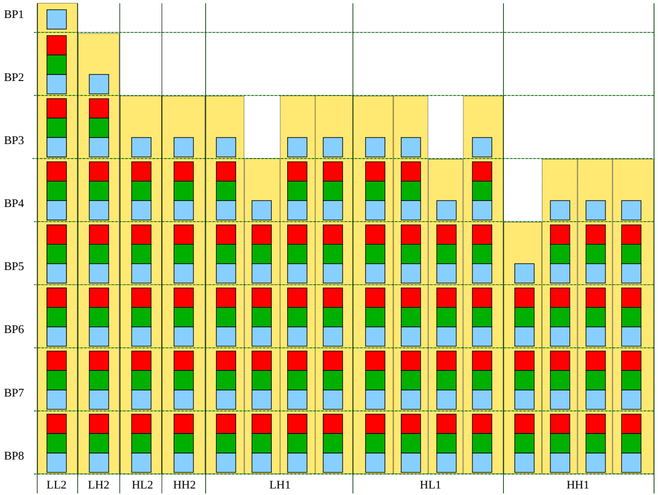
# Example of bit-rate allocation with EBCOT

## Allocation for maximal quality and medium resolution



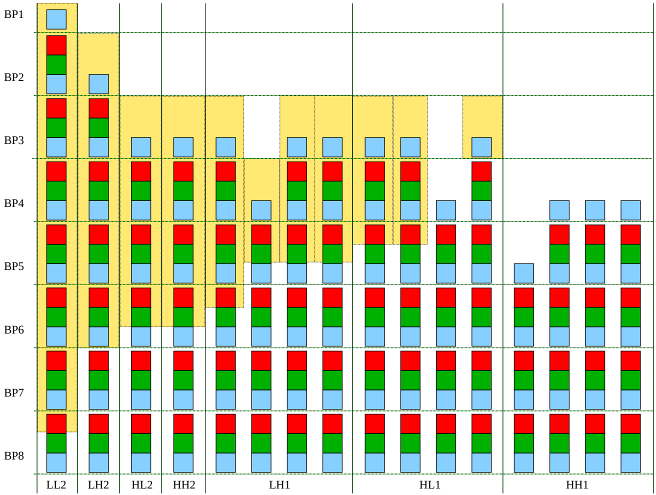
# Example of bit-rate allocation with EBCOT

## Allocation for maximal quality and maximal resolution



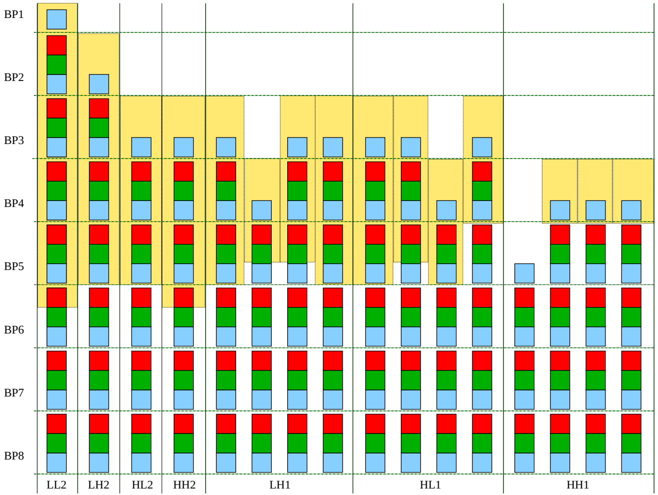
# Example of bit-rate allocation with EBCOT

## Allocation for perceptual quality and maximal resolution



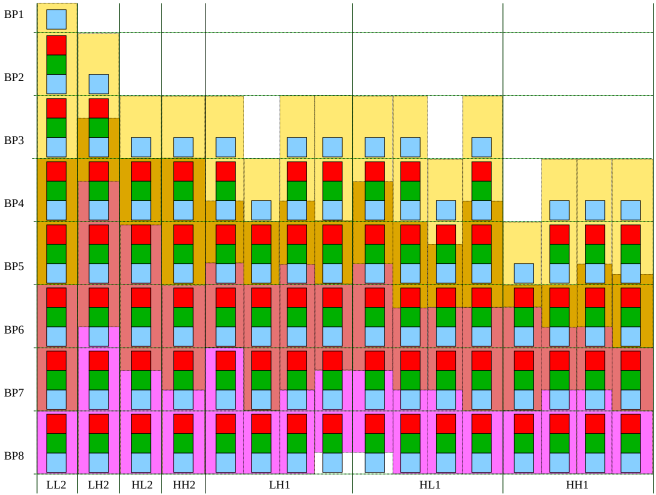
# Example of bit-rate allocation with EBCOT

## Allocation for a given bit-rate, maximal quality and resolution



# Example of bit-rate allocation with EBCOT

## Allocation pour several layers and maximal resolution



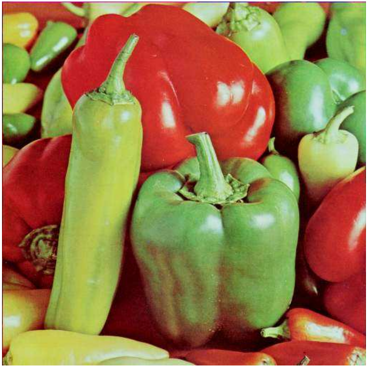
# JPEG

## Comparison JPEG / JPEG2000

Image Originale, 24 bpp

# Comparison JPEG / JPEG2000

## Rate: 1bpp



# Comparison JPEG / JPEG2000

## Rate: 0.75bpp

# Comparison JPEG / JPEG2000

Rate: 0.5bpp

# Comparison JPEG / JPEG2000

## Rate: 0.3bpp

# Comparison JPEG / JPEG2000

## Rate: 0.2bpp

# Comparison JPEG / JPEG2000

## Rate: 0.2bpp pour JPEG, 0.1 pour JPEG2000


# Error effect: JPEG

JPEG, $p_E = 10^{-4}$

JPEG, $p_E = 10^{-4}$

# Error effect: JPEG and JPEG 2000

JPEG, $p_E = 10^{-4}$

JPEG 2000, $p_E = 10^{-4}$

# Error effect: JPEG and JPEG 2000

JPEG, $p_E = 10^{-3}$

JPEG 2000, $p_E = 10^{-3}$

# Image coding and robustness

- Markers insertion
- Markers period
- Marker emulation prevention
- Trade-off between robustness and rate

# Error robustness in JPEG2000

- Data priorization is possible
- No dependency among codeblocks
  - No error propagation
- No block-based transform
  - No *blocking* artifacts