IMAGE SAMPLING AND IMAGE QUANTIZATION

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1. Introduction

![Image diagram showing the process of image sampling and quantization.](image)

**Fig 1** Image sampling and quantization / Analog image display
2. Sampling in the two-dimensional space

*Basics on image sampling*
**The concept of spatial frequencies**

- **Grey scale images** can be seen as a 2-D generalization of time-varying signals (both in the analog and in the digital case); the following equivalence applies:

<table>
<thead>
<tr>
<th>1-D signal (time varying)</th>
<th>2-D signal (grey scale image)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time coordinate t</td>
<td>Space coordinates x, y</td>
</tr>
<tr>
<td>Instantaneous value: f(t)</td>
<td>Brightness level, point-wise: f(x, y)</td>
</tr>
<tr>
<td>A 1-D signal that doesn’t vary in time (is constant) = has 0 A.C. component, and only a D.C. component</td>
<td>A perfectly uniform image (it has the same brightness in all spatial locations); the D.C. component = the brightness in any point</td>
</tr>
<tr>
<td>The frequency content of a 1-D signal is proportional to the speed of variation of its instantaneous value in time: ( \nu_{\text{max}} \sim \max(df/dt) )</td>
<td>The frequency content of an image (2-D signal) is proportional to the speed of variation of its instantaneous value in space: ( \nu_{\text{max},x} \sim \max(df/dx); \nu_{\text{max},y} \sim \max(df/dy) ) =&gt; ( \nu_{\text{max},x}, \nu_{\text{max},y} = \text{“spatial frequencies”} )</td>
</tr>
<tr>
<td>Discrete 1-D signal: described by its samples =&gt; a vector: ( \mathbf{u} = [u(0) \ u(1) \ \ldots \ u(N-1)] ), N samples; the position of the sample = the discrete time moment</td>
<td>Discrete image (2-D signal): described by its samples, but in 2-D =&gt; a matrix: ( \mathbf{U} = [M \times N] ), ( \mathbf{U} = {u(m,n)}, \ m=0,1,\ldots,M-1; \ n=0,1,\ldots,N-1. )</td>
</tr>
<tr>
<td>The spectrum of the time varying signal = the real part of the Fourier transform of the signal, ( F(\omega) ); ( \omega = 2\pi \nu )</td>
<td>The spectrum of the image = real part of the Fourier transform of the image = 2-D generalization of 1-D Fourier transform, ( F(\omega_x, \omega_y) ); ( \omega_x = 2\pi \nu_x; \omega_y = 2\pi \nu_y )</td>
</tr>
</tbody>
</table>
**Images of limited bandwidth**

- **Limited bandwidth image = 2-D signal with finite spectral support:**

  \[ F(v_x, v_y) = \text{the Fourier transform of the image:} \]
  
  \[
  F(v_x, v_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-j\omega_x x} e^{-j\omega_y y} \, dx \, dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-j2\pi(v_x x + v_y y)} \, dx \, dy.
  \]

  \[
  |F(v_x, v_y)|
  \]

  \[ F(v_x, v_y) = 0 \quad |v_x| > |v_{x0}|, \quad |v_y| > |v_{y0}|
  \]

  The Fourier transform of the limited spectrum image

  The spectral support region

  The spectrum of a limited bandwidth image and its spectral support
Two-dimensional sampling (1)

The common sampling grid = the uniformly spaced, rectangular grid:

Image sampling = read from the original, spatially continuous, brightness function \( f(x,y) \), only in the black dots positions (\( \Leftrightarrow \) only where the grid allows):

\[
g(\Delta x, \Delta y)(x, y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - m\Delta x, y - n\Delta y)
\]

\[
\Rightarrow f_s(x, y) = \begin{cases} f(x, y), & x = m\Delta x, y = n\Delta y, \\ 0, & \text{otherwise} \end{cases}, m, n \in \mathbb{Z}.
\]

\[
\Leftrightarrow f_s(x, y) = f(x, y)g(\Delta x, \Delta y)(x, y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(m\Delta x, n\Delta y)\delta(x - m\Delta x, y - n\Delta y)
\]
Two-dimensional sampling (2)

**Question:** How to choose the values \( \Delta x, \Delta y \) to achieve:
- the representation of the digital image by the min. number of samples,
- at (ideally) no loss of information?

(I. e.: for a perfectly uniform image, only 1 sample is enough to completely represent the image \( \Rightarrow \) sampling can be done with very large steps; on the opposite – if the brightness varies very sharply \( \Rightarrow \) very many samples needed)

\( \Rightarrow \) The sampling intervals \( \Delta x, \Delta y \) needed to have no loss of information depend on the spatial frequency content of the image.

\( \Rightarrow \) Sampling conditions for no information loss – derived by examining the spectrum of the image \( \Leftrightarrow \) by performing the Fourier analysis:

\[
F_S(v_x, v_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_S(x, y) e^{-j2\pi v_x x} e^{-j2\pi v_y y} \, dx \, dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) g(\Delta x, \Delta y)(x, y) e^{-j2\pi v_x x} e^{-j2\pi v_y y} \, dx \, dy.
\]

\( \Rightarrow \) The sampling grid function \( g(\Delta x, \Delta y) \) is periodical with period \( (\Delta x, \Delta y) \) \( \Rightarrow \) can be expressed by its Fourier series expansion:

\[
g(\Delta x, \Delta y)(x, y) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} a(k, l) \cdot e^{j2\pi \cdot \frac{k}{\Delta x} x} \cdot e^{j2\pi \cdot \frac{l}{\Delta y} y},
\]

where:

\[
a(k, l) = \frac{1}{\Delta x} \cdot \frac{1}{\Delta y} \int_{0}^{\Delta x} \int_{0}^{\Delta y} g(\Delta x, \Delta y)(x, y) e^{-j2\pi \cdot \frac{k}{\Delta x} x} \cdot e^{-j2\pi \cdot \frac{l}{\Delta y} y} \, dx \, dy.
\]
Since:

\[ g(\Delta x, \Delta y)(x, y) = \begin{cases} 
1, & \text{if } x = y = 0 \\
0, & \text{otherwise}
\end{cases} \]

Therefore the Fourier transform of \( f_S \) is:

\[
F_S(v_x, v_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \left( \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \frac{1}{\Delta x \cdot \Delta y} \cdot e^{\frac{j2\pi k x}{\Delta x}} \cdot e^{\frac{j2\pi l y}{\Delta y}} \right) \cdot e^{-j2\pi v_x x} \cdot e^{-j2\pi v_y y} \, dx \, dy
\]

\[
= \frac{1}{\Delta x \cdot \Delta y} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot \left( \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \cdot \right) \cdot e^{-j2\pi v_x x} \cdot e^{-j2\pi v_y y} \, dx \, dy
\]

\[
= \frac{1}{\Delta x \cdot \Delta y} \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot e^{-j2\pi v_x x} \cdot e^{-j2\pi v_y y} \, dx \, dy
\]

\[
= \frac{1}{\Delta x \cdot \Delta y} \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} F\left( v_x - \frac{k}{\Delta x}, v_y - \frac{l}{\Delta y} \right).
\]

\[ \Rightarrow \text{The spectrum of the sampled image = the collection of an infinite number of scaled spectral replicas of the spectrum of the original image, centered at multiples of spatial frequencies } 1/\Delta x, 1/\Delta y. \]
Digital image processing

Chapter 3. Image sampling and quantization

Original image

Original image spectrum – 3D

Original image spectrum – 2D

2-D rectangular sampling grid

Sampled image spectrum – 3D

Sampled image spectrum – 2D
Digital image processing

Chapter 3. Image sampling and quantization

Image reconstruction from its samples

Let us assume that the filtering region \( R \) is rectangular, at the middle distance between two spectral replicas:

\[
H(v_x, v_y) = \begin{cases} 
\frac{1}{(v_{xs}v_{ys})}, & |v_x| < \frac{v_{xs}}{2} \text{ and } |v_y| < \frac{v_{ys}}{2} \\
0, & \text{otherwise}
\end{cases}
\]

\[
h(x, y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f_s(m \Delta x, n \Delta y) h(x-m \Delta x, y-n \Delta y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f_s(m \Delta x, n \Delta y) \frac{\sin(\pi v_x m \Delta x)}{\pi v_x m \Delta x} \frac{\sin(\pi v_y n \Delta y)}{\pi v_y n \Delta y} \frac{\sin(\pi v_x m \Delta x)}{\pi v_x m \Delta x} \frac{\sin(\pi v_y n \Delta y)}{\pi v_y n \Delta y}
\]

Fig. 4 The sampled image spectrum

\[
v_{xs} > 2v_{x0}, \quad v_{ys} > 2v_{y0} \quad \Delta x < \frac{1}{2v_{x0}}, \Delta y < \frac{1}{2v_{y0}}
\]
Since the sinc function has infinite extent $\Rightarrow$ it is impossible to implement in practice the ideal LPF $\Rightarrow$ it is impossible to reconstruct in practice an image from its samples without error if we sample it at the Nyquist rates.

**Practical solution:** sample the image at higher spatial frequencies $+$ implement a real LPF (as close to the ideal as possible).
The Nyquist rate. The aliasing. The fold-over frequencies

Note: Aliasing may also appear in the reconstruction process, due to the imperfections of the filter!

How to avoid aliasing if cannot increase the sampling frequencies?
By a LPF on the image applied prior to sampling!

Fig. 5 Aliasing – fold-over frequencies

The Moire effect

“Jagged” boundaries
Non-rectangular sampling grids. Interlaced sampling grids

Interlaced sampling

Optimal sampling = Karhunen-Loeve expansion: \( f(x, y) = \sum_{m,n=0}^{\infty} a_{m,n} \Phi_{m,n} \)
The question is: what to fill in the “interpolated” (new) dots?
Several interpolation methods are available; ideally – sinc function in the spatial domain; in practice – simpler interpolation methods (i.e. approximations of LPFs).
### Image interpolation filters:

<table>
<thead>
<tr>
<th>The 1-D interpolation function</th>
<th>Graphical representation</th>
<th>( p(x) )</th>
<th>The 2-D interpolation function ( p_a(x,y) = p(x)p(y) )</th>
<th>Frequency response ( p_a(\xi,\eta) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectangular (zero-order filter) ( p_0(x) )</td>
<td><img src="image1.png" alt="Graph" /></td>
<td>( \frac{1}{\Delta x} \text{rect} \left( \frac{x}{\Delta x} \right) )</td>
<td>( p_0(x) \times p_0(y) )</td>
<td>sinc ( \left( \frac{\xi}{2\Delta x_{\eta}} \right) ) sinc ( \left( \frac{\eta}{2\Delta y_{\xi}} \right) )</td>
</tr>
<tr>
<td>Triangular (first order filter) ( p_1(x) )</td>
<td><img src="image2.png" alt="Graph" /></td>
<td>( \frac{1}{\Delta x} \triangledown \left( \frac{x}{\Delta x} \right) )</td>
<td>( p_1(x) \times p_1(y) )</td>
<td>[ \text{sinc} \left( \frac{\xi}{2\Delta x_{\eta}} \right) \text{sinc} \left( \frac{\eta}{2\Delta y_{\xi}} \right) ]</td>
</tr>
<tr>
<td>n-order filter ( p_n(x) )</td>
<td><img src="image3.png" alt="Graph" /></td>
<td>( p_0(x) \otimes \cdots \otimes p_0(x) )</td>
<td>( p_n(x) \times p_n(y) )</td>
<td>[ \text{sinc} \left( \frac{\xi}{2\Delta x_{\eta}} \right) \text{sinc} \left( \frac{\eta}{2\Delta y_{\xi}} \right) e^{\text{n convolui}} ]</td>
</tr>
<tr>
<td>Gaussian ( p_g(x) )</td>
<td><img src="image4.png" alt="Graph" /></td>
<td>( \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[ -\frac{x^2}{2\sigma^2} \right] )</td>
<td>( \exp \left[ -2\pi^2\sigma^2 \left( \frac{\xi^2}{2\Delta x_{\eta}} + \frac{\eta^2}{2\Delta y_{\xi}} \right) \right] )</td>
<td></td>
</tr>
</tbody>
</table>
Image interpolation examples:

1. Rectangular (zero-order) filter, or nearest neighbour filter, or box filter:

![Graph of rectangular filter]

Original | Sampled | Reconstructed
Image interpolation examples:

2. Triangular (first-order) filter, or *bilinear filter*, or *tent filter*:
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Image interpolation examples:

3. Cubic interpolation filter, or *bicubic filter* – begins to better approximate the sinc function:
Practical limitations in image sampling and reconstruction

Fig. 7 The block diagram of a real sampler & reconstruction (display) system

Fig. 8 The real effect of the interpolation
3. Image quantization

3.1. Overview

Fig. 9 The quantizer’s transfer function
3.2. The uniform quantizer

The quantizer’s design:

- Denote the input brightness range: \( u \in [l_{\text{min}}; L_{\text{Max}}] \)
- Let \( B \) – the number of bits of the quantizer => \( L = 2^B \) reconstruction levels
- The expressions of the decision levels:

\[
t_1 = l_{\text{min}}; \quad t_{L+1} = L_{\text{Max}}
\]

\[
t_k - t_{k-1} = t_{k+1} - t_k = \text{constant} = q
\]

\[
q = \frac{L_{\text{Max}} - l_{\text{min}}}{L}, t_k = t_{k-1} + q \Rightarrow q = \frac{L_{\text{Max}} - l_{\text{min}}}{L}
\]

- The expressions of the reconstruction levels:

\[
r_k = \frac{t_k + t_{k+1}}{2} \Rightarrow r_k = t_k + \frac{q}{2}
\]

- Computation of the quantization error: for a given image of size \( M \times N \) pixels, \( U \) – non-quantized, and \( U' \) – quantized => we estimate the MSE:

\[
\varepsilon = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (u(m,n) - u'(m,n))^2 = \sum_{k=1}^{L} \int_{t_k}^{t_{k+1}} (u - r_k)^2 h_{\text{lin},U}(u)du
\]
Examples of uniform quantization and the resulting errors:

\[ B = 1 \Rightarrow L = 2 \]

Non-quantized image

Quantized image

Quantization error; MSE = 36.2

The histogram of the non-quantized image
Examples of uniform quantization and the resulting errors:

B=2 => L=4

Non-quantized image

Quantized image

Quantization error; MSE=15

The histogram of the non-quantized image
Examples of uniform quantization and the resulting errors:

\( B = 3 \Rightarrow L = 8 \); false contours present

Non-quantized image

Quantized image

Quantization error; \( \text{MSE} = 7.33 \)

The histogram of the non-quantized image
3.2. The optimal (MSE) quantizer (the Lloyd-Max quantizer)

\[ e = E[(u - u')^2] = \int (u - u')^2 h_u(u)du \quad \rightarrow \quad e = \sum_{i=1}^{L} (u - r_i)^2 h_u(u)du \]

\[ \frac{\partial e}{\partial r_k} = \left( (t_k - r_{k-1})^2 - (t_k - r_k)^2 \right) h_u(t_k) = 0 \]

\[ \frac{\partial e}{\partial r_k} = -2 \int_{t_i}^{t_{i+1}} (u - r_k) h_u(u)du = 0 \quad 1 \leq k \leq L \]

\[ t_k = \frac{r_k + r_{k-1}}{2} \quad r_k = \frac{\int_{t_i}^{t_{i+1}} u h_u(u)du}{\int_{t_i}^{t_{i+1}} h_u(u)du} = E[u | u \in \mathcal{G}_k] \]

\[ p_u(u) \approx p_u(\hat{t}_j), \quad \hat{t}_j = \frac{1}{2} (t_j + t_{j+1}), \quad t_j \leq u < t_{j+1} \]

\[ A \int [h_u(u)]^{-1/3} du \]

\[ t_{k+1} \approx \frac{\int_{t_i}^{t_{i+1}} h_u(u)du}{\int_{t_i}^{t_{i+1}} [h_u(u)]^{-1/3} du} + t_1 \]
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\[ \varepsilon = \frac{1}{12L^2} \left[ \int_{t_i}^{t_i} [h_u(u)]^{1/3} du \right]^3 \]

\[ h_u(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{(u-\mu)^2}{2\sigma^2} \right) \] (Gaussian), or \[ h_u(u) = \frac{\alpha}{2} \exp \left( -\alpha |u - \mu| \right) \] (Laplacian)

\[ \sigma^2 = \frac{2}{\alpha} \] (variance, \( \mu \)-mean)
Examples of optimal quantization and the quantization error:

\[ B = 1 \Rightarrow L = 2 \]

Non-quantized image

Quantized image

The quantization error; MSE = 19.5

The evolution of MSE in the optimization, starting from the uniform quantizer

The non-quantized image histogram
Examples of optimal quantization and the quantization error:

$B=2 \implies L=4$

The quantization error; $\text{MSE}=9.6$

The evolution of MSE in the optimization, starting from the uniform quantizer
Examples of optimal quantization and the quantization error:

\( B = 3 \Rightarrow L = 8 \)

Non-quantized image

Quantized image

The quantization error; \( \text{MSE} = 5 \)

The evolution of MSE in the optimization, starting from the uniform quantizer

The non-quantized image histogram
3.3. The uniform quantizer = the optimal quantizer for the uniform grey level distribution:

\[
 h_u(u) = \begin{cases} 
 1 & t_1 \leq u \leq t_{L+1} \\
 t_{L+1} - t_1 & \\
 0 & \text{otherwise} 
\end{cases}
\]

\[
 r_k = \frac{(t_{k+1}^2 - t_k^2)}{2(t_{k+1} - t_k)} = \frac{t_{k+1} + t_k}{2}
\]

\[
 t_k = \frac{t_{k+1} + t_{k-1}}{2} \quad \text{and} \quad t_k - t_{k-1} = t_{k+1} - t_k = \text{constant} = q
\]

\[
 q = \frac{t_{L+1} - t_1}{L}, \quad t_k = t_{k-1} + q, \quad r_k = t_k + \frac{q}{2}
\]

\[
 \varepsilon = \frac{1}{q} \int_{-q/2}^{q/2} u^2 du = \frac{q^2}{12}
\]

\[
 \frac{\varepsilon}{\sigma_u^2} = 2^{-2^B}, \text{therefore } \text{SNR} = 10 \log_{10} 2^2 = 6 \cdot B \text{ dB}
\]
3.4. Visual quantization methods

- In general – if $B<6$ (uniform quantization) or $B<5$ (optimal quantization) => the "contouring" effect (i.e. false contours) appears in the quantized image.
- The false contours ("contouring") = groups of neighbor pixels quantized to the same value => regions of constant gray levels; the boundaries of these regions are the false contours.
- The false contours do not contribute significantly to the MSE, but are very disturbing for the human eye => it is important to reduce the visibility of the quantization error, not only the MSQE. ⇒ Solutions: visual quantization schemes, to hold quantization error below the level of visibility. ⇒ Two main schemes: (a) contrast quantization; (b) pseudo-random noise quantization
3.4. Visual quantization methods

a. Contrast quantization

- The visual perception of the luminance is non-linear, but the visual perception of contrast is linear
  \( \Rightarrow \) uniform quantization of the contrast is better than uniform quantization of the brightness
  \( \Rightarrow \) contrast = ratio between the lightest and the darkest brightness in the spatial region
  \( \Rightarrow \) just noticeable changes in contrast: 2% \( \Rightarrow \) 50 quantization levels needed \( \Leftrightarrow \) 6 bits needed with a uniform quantizer (or 4-5 bits needed with an optimal quantizer)

\[
c = \alpha \ln(1 + \beta u), 0 \leq u \leq 1; \text{typ.} \alpha = 6...18, \beta = \frac{\alpha}{\ln(1 + \beta)}
\]

or

\[
c = \alpha u^{\beta}; \text{typ.} \alpha = 1; \beta = 1/3
\]
Examples of contrast quantization:

- For \( c = u^{1/3} \):
Examples of contrast quantization:

- For the log transform:

```
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
```

```
0 50 100 150 200 250
0
100
200
300
400
500
600
700
800
900
1000
```

The transfer function of the contrast quantizer
Decision levels  Reconstruction levels

t1=0  t2=46.0273  t3=102.2733  t4=171.0068  t5=255
b. Pseudorandom noise quantization ("dither")

$$u(m,n) + v(m,n) \rightarrow \text{K bits quantizer} \rightarrow v'(m,n) \rightarrow u'(m,n)$$

Uniformly distributed pseudorandom noise, $$[-A,A]$$

Prior to dither subtraction

Large dither amplitude

Uniform quantization, $$B=4$$

Small dither amplitude
Fig. 13

a. 3 bits quantizer => visible false contours;
b. 8 bits image, with pseudo-random noise added in the range \([-16, 16]\);
c. the image from Figure b) quantized with a 3 bits quantizer

d. the result of subtracting the pseudo-random noise from the image in Figure c)
Halftone images generation

Fig.14 Digital generation of halftone images

Luminance $v(m,n)$

$0 \leq u(m,n) \leq A$

Thresholding $v'(m,n)$

$0 \leq \eta(m,n) \leq A$

Pseudorandom matrix

$H_1 = \begin{bmatrix}
40 & 60 & 150 & 90 & 10 \\
80 & 170 & 240 & 200 & 110 \\
140 & 210 & 250 & 220 & 130 \\
120 & 190 & 230 & 180 & 70 \\
20 & 100 & 160 & 50 & 30
\end{bmatrix}$

$H_2 = \begin{bmatrix}
52 & 44 & 36 & 124 & 132 & 140 & 148 & 156 \\
60 & 4 & 28 & 116 & 200 & 228 & 236 & 164 \\
68 & 12 & 20 & 108 & 212 & 252 & 244 & 172 \\
76 & 84 & 92 & 100 & 204 & 196 & 188 & 180 \\
132 & 140 & 148 & 156 & 52 & 44 & 36 & 124 \\
200 & 228 & 236 & 164 & 60 & 4 & 28 & 116 \\
212 & 252 & 244 & 172 & 68 & 12 & 20 & 108 \\
204 & 196 & 188 & 180 & 76 & 84 & 92 & 100
\end{bmatrix}$

Demo: [http://markschulze.net/halftone/index.html](http://markschulze.net/halftone/index.html)

Fig.15 Halftone matrices
Fig. 3.16

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Color images quantization

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Fig. 17 Color images quantization