Analog to Digital Conversion

from the Perspective of Pattern Recognition

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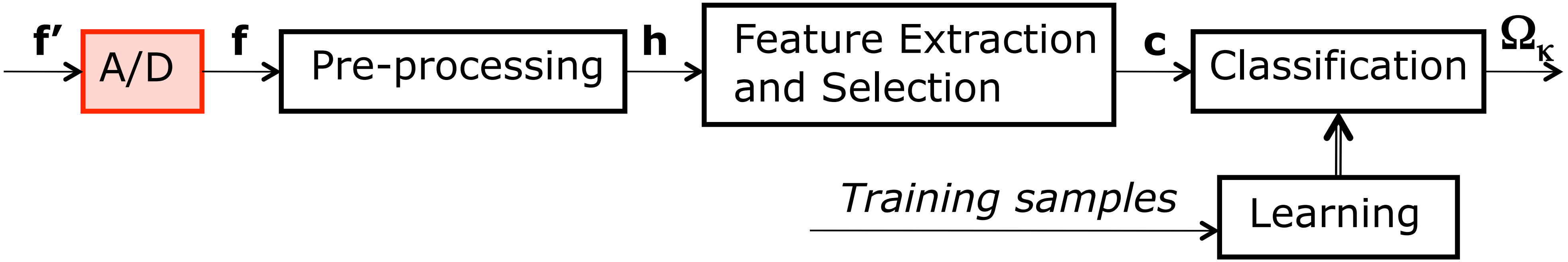
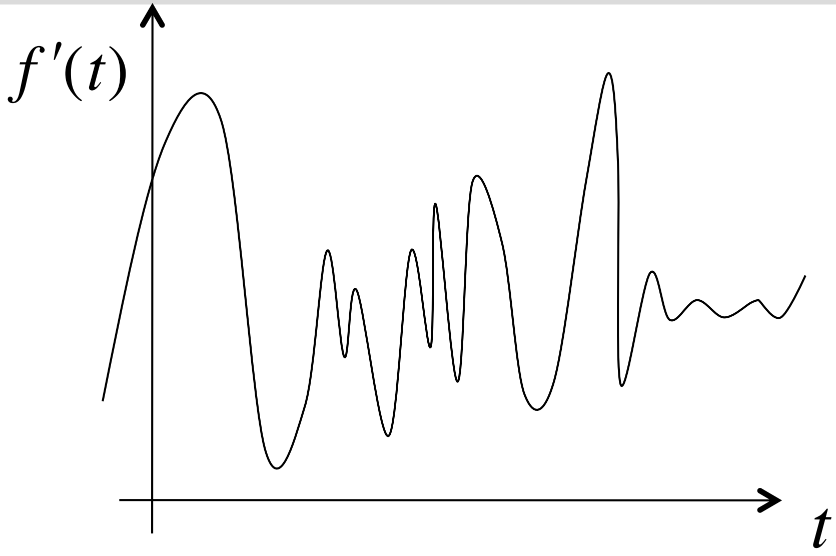
Pattern Recognition Pipeline



- The goal of analog to digital conversion is to gather sensed data f' and change it to a representation that is amenable to further digital processing.

Need for A/D Conversion



- Continuous range of t values
- Continuous range of amplitude $f'(t)$ values.
- We can only store a finite amount of values
- in a finite number of bits (discrete values).
- Goal: Find a discrete representation such that the original analog signal can be accurately reconstructed.

On Accuracy

- We want to have the analog signal accurately reconstructed.
- What is accurate?

On Accuracy

- We want to have the analog signal accurately reconstructed.
- What is accurate? Ideally no loss of information
- Sometimes in order to get better speeds we accept some minimal information loss.
- We often have to face trade-offs:
  - voice recording were you skip letters
  - digital images with aliasing effects
  - movies with blocky look

The two Aspects of A/D Conversion

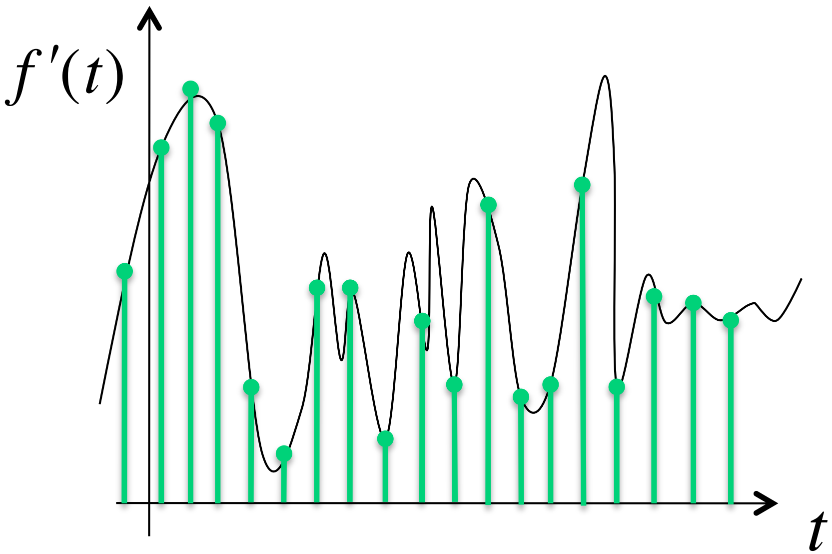
- The function $f'(t)$ must be represented by a *vector* or by a *sequence of numbers* $\vec{f}$ using a *finite* number of values.
- For higher dimensional signals, like an image, the input function $f'(x,y)$ must be represented by a *vector* or by a *sequence of numbers* $\vec{f}$ at distinct locations (i,j). At each such location there is only a *finite* number of values that can be stored.
- In the context of pictures:
  - How many pixels do I need? (How many (i,j) locations?)
  - How many bits per pixel

A/D Conversion Steps

- The A/D conversion (coding) involves:

1. measuring the amplitude values (or function values) at a finite number of positions:

   sampling,



2. representing the amplitude values by a finite number of natural numbers:

   quantization

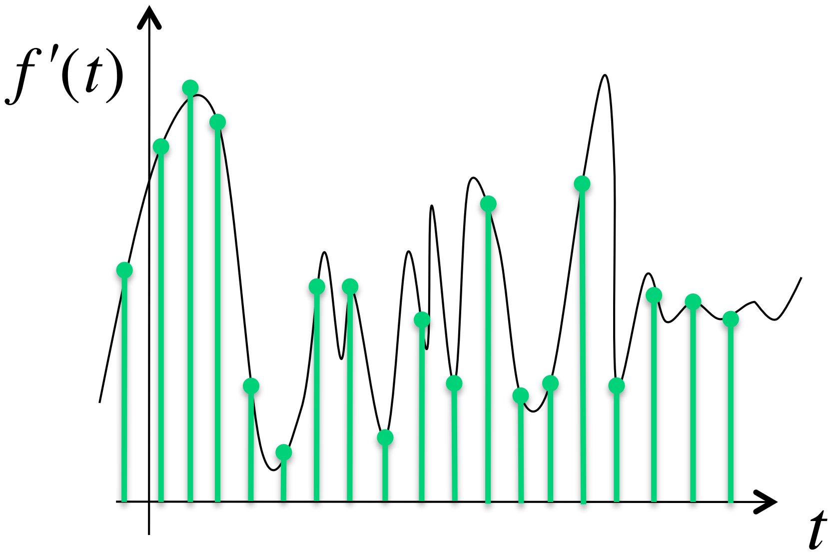
Sampling Issues

- We could have different sampling steps along the sampling axis, but in most cases we assume

  Regular (equidistant) sampling.

- Even under regular sampling, one must decide:

  - Where do we take the samples along the analog signal so that we can properly reconstruct the original function.
  - In other words: What is the sampling interval dt or dx?



Quantization Issues

- Along the vertical axis we also have continuous values that we can only store using a finite number of natural numbers.
- Typical image options:
  - 8-12 bits per pixel for grayscale images
  - 8 bits per color channel (R,G,B) per pixel for color images
  - 1 bit per pixel for black/white images
  - special encoding per application
- Unlike sampling, quantization intervals are often not equidistant.
- In the case of non-uniform quantization, the behavior of the quantizer is decided by the characteristic function.

A/D Analysis Tools

- Important questions:
  1. How do we decide the sampling rate?
  2. How do we derive characteristic function of the quantizer?
  3. How can these affect my pattern recognition system?
- In order to fulfill the necessary performance guarantees (accurate reconstruction) we need to use the appropriate tools.
- Sampling Tool: Fourier Analysis

  Fourier Analysis allows us to study signals as a collection of periodic signals. This periodicity then guides the sampling rate.
- Quantization Tool: Probability Theory

  Study previous behavior of the signal. High probability values use dense quantization. Lower probability values use sparse quantization.

Fourier Analysis

- Based on the Fourier series.
- The original theory showed how any periodic function can be decomposed to a set of sines and cosines.
- The theory was generalized for non-periodic functions.
- Through the Fourier analysis we have a technique of decomposing complex patterns into a collection of simpler patterns.

Fourier Transform

- How do we find the underlying sines and cosines of a function $f(x)$?
- In other words how do we get the Fourier series of $f(x)$?
- Using the Fourier Transform:

$$\mathcal{F}(\omega) = \mathrm{FT}\{f(x)\} = \int_{-\infty}^{\infty} f(x) e^{-j\omega x} dx$$

where $\mathcal{F}(\omega)$ is the signal in the frequency domain and ω is the frequency of the sinusoidal wave.

Note: the signal must be absolutely integrable, $\int_{-\infty}^{\infty} |f(x)| dx < \infty$

- Given $\mathcal{F}(\omega)$, how do we get the original signal $f(x)$ back?
- Using the Inverse Fourier Transform:

$$f(x) = \mathrm{FT}^{-1}\{\mathcal{F}(\omega)\} = \frac{1}{2\pi} \int_{-\infty}^{\infty} \mathcal{F}(\omega) e^{jx\omega} d\omega$$

Fourier Series

- A periodic function $f(x)$ has the Fourier series

$$\mathcal{F}(\omega) = \sum_{k=-\infty}^{\infty} a_k e^{2\pi j\left(\frac{k\omega}{2\omega_0}\right)}$$

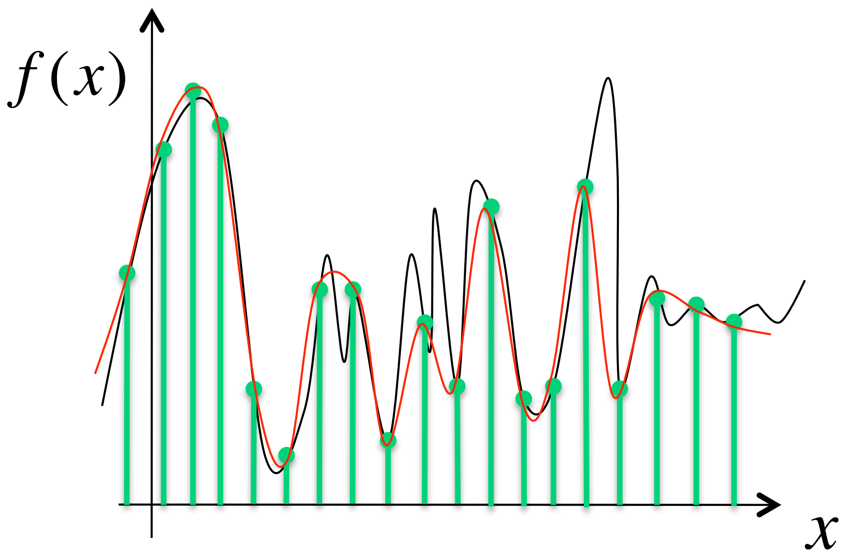
where ω_0 is the periodicity of the signal and a_k are the Fourier coefficients.

$$a_k = \frac{1}{2\omega_0} \int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{-2\pi j\left(\frac{k\omega}{2\omega_0}\right)} d\omega$$

Note: Though both equations have $\mathcal{F}(\omega)$, the Fourier coefficients a_k have a band-limited integral, which can be evaluated. Thus a_k becomes a function of ω.

The Importance of Nyquist Sampling Thrm

- This theorem provides a theoretical sampling rate at which we will incur (under certain conditions) no loss of information.



- High sampling rate leads to too much data.
- Low sampling rate leads to loss of information.

Band-Limited Function

- A function $f(x)$ is band-limited in the frequency range $(-B_x, B_x)$, if $\mathcal{F}(\omega) = 0$ for $|\omega| > \omega_0 = 2\pi B_x$ where ω_0 is the boundary frequency.
- What is so special about frequency band limited functions?
- They are restricted to a finite range of frequencies.
- Band limited => finite number of sin and cos terms

  => finite number of coefficients

  => signal can be reconstructed from a limited number of discrete samples.

Nyquist Sampling Theorem

- Let $f(x)$ be a band-limited function in the frequency range $(-B_x, B_x)$.
- Then $f(x)$ is completely determined by the samples

$$f_k = f(k\,\Delta x) \quad \text{where } k = 0, \pm 1, \pm 2, \ldots$$

if the sampling interval is chosen as

$$\Delta x \leq \frac{1}{2B_x} = \frac{\pi}{\omega_0}$$

- The original signal $f(x)$ can be reconstructed without any error using the following interpolation

$$f(x) = \sum_{k=-\infty}^{\infty} f_k \frac{\sin(2\pi B_x(x - k\Delta x))}{2\pi B_x(x - k\Delta x)} = \sum_{k=-\infty}^{\infty} f_k \operatorname{sinc}(2\pi B_x(x - k\Delta x))$$

Main Idea of Proof

- Goal: To show that by using the sampling rate recommended by Nyquist's sampling theorem, we incur no information loss.

- We want to show that the $f(x)$ we reconstruct from the samples f_k is identical to the original *band-limited* signal.

- We will use the Fourier Transform, the Inverse Fourier Transform and the Fourier Series to prove the theorem.

- Recall that for a band-limited signal $\mathcal{F}(\omega) = 0$ for $|\omega| > \omega_0 = 2\pi B_x$

Step 1

- If we had the Fourier Transform of the reconstructed signal, $\mathcal{F}(\omega)$, we could compute $f(x)$ via the Inverse Fourier Transform, as follows:

$$f(x) = \mathrm{FT}^{-1}\{\mathcal{F}(\omega)\} = \frac{1}{2\pi}\int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{jx\omega} d\omega$$

- Problem: We don't have $\mathcal{F}(\omega)$.

- If we treat $f(x)$ as a periodic signal with period ω_0, we can get $\mathcal{F}(\omega)$ using the Fourier Series representation.

Step 2

- In order to use the Fourier Series representation we need the Fourier coefficients.

$$a_k = \frac{1}{2\omega_0} \int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{-2\pi j\left(\frac{k\omega}{2\omega_0}\right)} d\omega$$

- Rewrite this equation so that it looks like an Inverse Fourier Transform ($f(x) = \mathrm{FT}^{-1}\{\mathcal{F}(\omega)\} = \frac{1}{2\pi}\int_{-\infty}^{\infty} \mathcal{F}(\omega) e^{jx\omega} d\omega$).

$$a_k = \frac{\pi}{2\pi\omega_0} \int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{j\omega\left(\frac{-2\pi k}{2\omega_0}\right)} d\omega$$

Step 2 - continued

- The Fourier series coefficients are now:

$$a_k = \frac{1}{2\pi}\frac{\pi}{\omega_0}\int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{j\omega\left(\frac{-k\pi}{\omega_0}\right)} d\omega$$

- But according to the Inv. FT, $f(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \mathcal{F}(\omega) e^{j\omega x} d\omega$. Thus:

$$a_k = \frac{\pi}{\omega_0} f\left(-\frac{k\pi}{\omega_0}\right)$$

- The Nyquist Sampling theorem recommends a sampling rate of $\Delta x \leq 1/(2B_x) = \pi/\omega_0$. If we use such a sampling rate:

$$a_k = \Delta x\, f(-k\,\Delta x)$$

Step 3

- Take the a_k and put them back in the Fourier series and hopefully we get the Fourier Series to look like an interpolation formula.

$$\mathcal{F}(\omega) = \sum_{k=-\infty}^{\infty} a_k e^{2\pi j\left(\frac{k\omega}{2\omega_0}\right)}$$

$$\mathcal{F}(\omega) = \sum_{k=-\infty}^{\infty} \Delta x\, f(-k\,\Delta x) e^{jk\omega\Delta x}$$

- Via a variable substitution we get:

$$\mathcal{F}(\omega) = \sum_{k=-\infty}^{\infty} \Delta x\, f(k\,\Delta x) e^{-jk\omega\Delta x}$$

Step 4

- Now we have an estimate of the Fourier Transform that we obtained directly from our discrete samples.
- We are ready to use the Inverse Fourier Transform to see which signal we reconstruct from these samples.

$$f(x) = \frac{1}{2\pi} \int_{-\omega_0}^{\omega_0} \mathcal{F}(\omega) e^{jx\omega} d\omega = \frac{1}{2\pi} \int_{-\omega_0}^{\omega_0} \left(\sum_{k=-\infty}^{\infty} \Delta x\, f(k\,\Delta x) e^{-jk\omega\Delta x} \right) e^{jx\omega} d\omega$$

$$f(x) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \Delta x\, f(k\,\Delta x) \int_{-\omega_0}^{\omega_0} e^{-jk\omega\Delta x} e^{jx\omega} d\omega$$

$$f(x) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \Delta x\, f(k\,\Delta x) \int_{-\omega_0}^{\omega_0} e^{j\omega(x-k\Delta x)} d\omega$$

Step 4 - continued

- We can then evaluate the integral

$$f(x) = \sum_{k=-\infty}^{\infty} \frac{\Delta x}{2\pi} f(k\,\Delta x) \left[\frac{e^{j\omega(x-k\Delta x)}}{j(x-k\Delta x)} \right]_{-\omega_0}^{\omega_0}$$

$$f(x) = \sum_{k=-\infty}^{\infty} \frac{\Delta x}{2\pi} f(k\,\Delta x) \left(\frac{1}{j} \right) \left(\frac{e^{j\omega_0(x-k\Delta x)} - e^{-j\omega_0(x-k\Delta x)}}{(x-k\Delta x)} \right)$$

- Recall that $\sin\theta = \frac{1}{2j}\left(e^{j\theta} - e^{-j\theta}\right)$. Hence

$$f(x) = \sum_{k=-\infty}^{\infty} \frac{\Delta x}{2\pi} f(k\,\Delta x) \frac{2\sin(\omega_0(x-k\Delta x))}{(x-k\Delta x)}$$

Step 4 – last part

- If we have $f_k = f(k\,\Delta x)$ and $\Delta x = \dfrac{1}{2B_x}$ and $\omega_0 = 2\pi B_x$

$$f(x) = \sum_{k=-\infty}^{\infty} f(k\,\Delta x)\frac{\Delta x}{\pi}\frac{\sin(\omega_0(x - k\Delta x))}{(x - k\Delta x)}$$

$$f(x) = \sum_{k=-\infty}^{\infty} f_k \frac{\sin(2\pi B_x(x - k\Delta x))}{2\pi B_x(x - k\Delta x)}$$

- Thus, if we use the Nyquist sampling rate, we can reconstruct the original signal by interpolating the discrete samples.

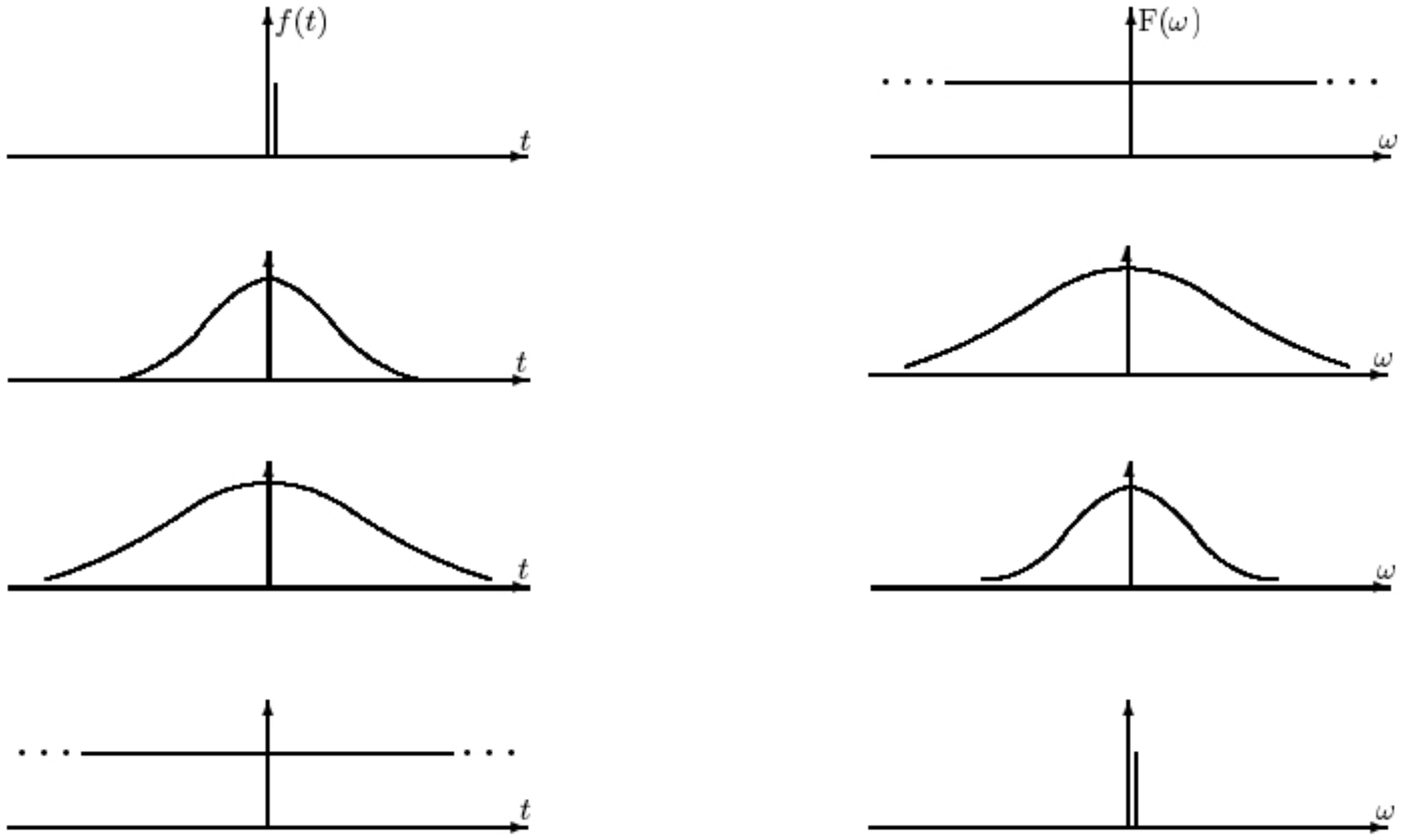
On the Nyquist Samping Theorem

- So, the **precise** reconstruction of f(x) requires:
  - an sampling interval $\Delta x = \frac{1}{2B_x}$
  - an infinite number of samples.

- In practice we are usually dealing with limited time, so we typically prefilter the signal and choose $\Delta x < \frac{1}{2B_x}$.
- Theorem: There is no function (in L_2), which is both band-limited and time-limited (except for the identity function).

- The smaller the function in the spatio-temporal domain, the larger it is in the frequency domain and vice versa.

Temporal vs. Frequency Domain



- Compromise between accuracy of representation (high prec., many samples, small intervals) storage requirements (little storage, few samples, large intervals).

Sampling in 2D

- We need to sample in each direction.
- $f(x,y)$ is coded as $f_{j,k}$ where

$$f_{j,k} = f(x_0 + \Delta x, y_0 + \Delta y)$$

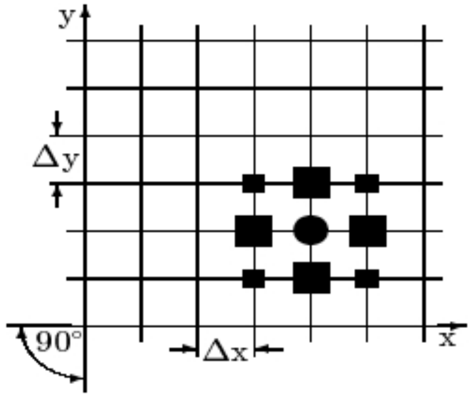
$$\text{where} \quad j = 0,1,\ldots,M_x - 1 \qquad k = 0,1,\ldots,M_y - 1$$

- We typically set $x_0 = y_0 = 0$ and $\Delta x = \Delta y = 1$ resulting in $f_{j,k} = f(j,k)$.
- Such a sampling setup results in a uniform sampling grid.

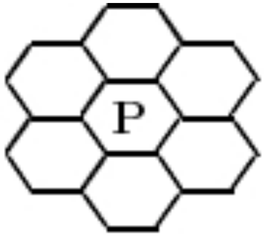
Uniform Sampling Grids

- There are 3 uniform sampling grids on a plane:

1. Square grid



2. Hexagon grid



3. Triangle-based grid