Time & Frequency Domain Measurements

H. Schmickler, CERN

Using several slides from:

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R. Jones (CERN)
T. Lefevre (CERN)
H. Damerau (CERN)
S. Zorzetti (FNAL)
Part I

- **Introduction:** What is time domain and frequency domain?

- Fourier synthesis and Fourier transform
- Time domain sampling of electrical signals (ADCs)
- Bunch signals in time and frequency domain
  - a) single bunch single pass
  - b) single bunch multi pass (circular accelerator)
  - c) multi bunch multi pass (circular accelerator)

- Oscillations within the bunch (head-tail oscillations) → advanced course
Part II

- Fourier transform of time sampled signals
  a) basics
  b) aliasing
  c) windowing
- Methods to improve the frequency resolution
  a) interpolation
  b) fitting (the NAFF algorithm)
  c) influence of signal to noise ratio
  d) special case: no spectral leakage + IQ sampling
- Analysis of non stationary spectra:
  - STFT (:= Short time Fourier transform) (Gabor transform)
    also called: Sliding FFT, Spectogram
  - wavelet analysis
  - PLL tune tracking
At first: everything happens in time domain, i.e. we exist in a 4D world, where 3D objects change or move as a function of time.

And we have our own sensors, which can watch this time evolution: eyes → bandwidth limit: 1 Hz

For faster or slow processes we develop instruments to capture events and look at them: oscililloscopes, stroboscopes, cameras...
• But we have another sensor: ears

• What is this?
• Once we perceive the material in frequency domain (our brain does this for us), we can better understand the material.

  • Essential:

Non matter whether we describe a phenomenon in time domain or in frequency domain, we describe the same physical reality. But the proper choice of description improves our understanding!
Had crazy idea (1807):

- **Any** periodic function can be rewritten as a weighted sum of **Sines** and **Cosines** of different frequencies.

Don’t believe it?
- Neither did Lagrange, Laplace, Poisson and other big wigs
- Not translated into English until 1878!

But it’s true!
- called **Fourier Series**
- Possibly the greatest tool used in Engineering
A periodic function $f(x)$ can be expressed as a series of harmonics, weighted by Fourier coefficients $c_n$.

$$f(x) = \sum_{n=-\infty}^{+\infty} c_n e^{-2i\pi \frac{n}{T} x}$$

$$c_n = \frac{1}{T} \int_{-\frac{T}{2}}^{+\frac{T}{2}} f(x) e^{-2i\pi \frac{n}{T} x} \, dx$$
Fourier Transform

• Also, defined as:

\[ F(u) = \int_{-\infty}^{\infty} f(x)e^{-iux} \, dx \]

Note: \( e^{ik} = \cos k + i \sin k \quad i = \sqrt{-1} \)

• Inverse Fourier Transform (IFT)

\[ f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(u)e^{iux} \, dx \]
Fourier Transform Pairs (I)

**FOURIER TRANSFORM PAIRS**

<table>
<thead>
<tr>
<th>$f(x)$</th>
<th>$F(u)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectangle function</td>
<td>Sinc function</td>
</tr>
<tr>
<td>$\text{Rect}(x)$</td>
<td>$\text{Sinc} , (u) = \frac{\sin \pi u}{\pi u}$</td>
</tr>
<tr>
<td>Triangle function</td>
<td>$\text{Sinc}^2 , (u)$</td>
</tr>
<tr>
<td>$\text{Unit impulse} , \delta(x)$</td>
<td>$\frac{1}{2} \delta(u) + \frac{1}{2\pi i u}$</td>
</tr>
<tr>
<td>Exponential Gaussian</td>
<td></td>
</tr>
<tr>
<td>$e^{-\alpha</td>
<td>x</td>
</tr>
<tr>
<td>$e^{-\alpha x^2}$</td>
<td>$\frac{\pi}{\alpha} e^{-\pi u^2/\alpha}$</td>
</tr>
</tbody>
</table>
Fourier Transform Pairs (II)

Comb function

$$\sum_{n=-\infty}^{\infty} \delta(x-nx_0)$$

$$\frac{1}{x_0} \sum_{n=-\infty}^{\infty} \delta(\xi-\frac{n}{x_0})$$

$$\frac{-2}{x_0} \quad \frac{-1}{x_0} \quad \frac{1}{x_0} \quad \frac{2}{x_0}$$

Cos term

$$\cos 2\pi \omega_0 x$$

$$\frac{1}{2} \left[ \delta(\xi-\omega_0) + \delta(\xi+\omega_0) \right]$$

$$\frac{1}{2} j \left[ -\delta(\xi-\omega_0) + \delta(\xi+\omega_0) \right]$$

Im F

Sin term

$$\sin 2\pi \omega_0 x$$

CAS 2019 H. Schmickler
In real accelerators not all available RF-buckets are filled with particle bunches.
- a gap must be left for the injection/extraction kickers
- Physics experiments can impose a minimum bunch distance, which is larger than one RF period (i.e. LHC)

Revolution frequency: \( \omega_{\text{rev}} = 2\pi f_{\text{rev}} \)

RF frequency: \( \omega_{\text{RF}} = 2\pi f_{\text{RF}} = h \times \omega_{\text{rev}} \) \( (h=\text{harmonic number}) \)

Bunch Repetition frequency: \( \omega_{\text{rep}} = 2\pi f_{\text{rep}} = \omega_{\text{rev}} / n \) \( (n=\text{number of RF buckets between bunches}) \)

\( f_{\text{rep}} = 1/\text{bunch spacing} \)
Nominal LHC Filling Scheme


Figure 1: Schematic of the Bunch Disposition around an LHC Ring for the 25ns Filling Scheme
Understanding beam signals in time and frequency domain

We start with:

**Single bunch single pass**

- Time and frequency domain description
- Measurement of bunch length in time domain  
  ➔ Sampling electrical signals with ADCs
- Measurement of bunch length in frequency domain
Particle beam with gaussian longitudinal distribution

**Time domain**

\[ f(t) = A_0 \exp \left( -\frac{t^2}{2\sigma_t^2} \right) \]

\[ \text{area} = \int_{-\infty}^{+\infty} f(t) \, dt = \sqrt{2\pi} A_0 \sigma_t \]

**Frequency domain**

\[ F(k) = \frac{A_0}{\sqrt{2\pi\sigma_f}} \exp \left( -\frac{k^2}{2\sigma_f^2} \right) \]

\[ \sigma_f = \frac{1}{2\pi\sigma_t} \]

\[ F(0) = \text{area} = \frac{A_0}{\sqrt{2\pi\sigma_f}} = \sqrt{2\pi} A_0 \sigma_t \]
Time domain measurement of single bunch

- Sampling (=measurement) of an electrical signal in regular time intervals. The electrical signal is obtained from a monitor, which is sensitive to the particle intensity.
Frequency domain measurement of single bunch

Nice example from R&D work in CTF3 (CERN)
A.Dabrowski et al., Proc of PAC07, FRPMS045

Primary signal is EM wave of beam extracted through a thin window

Subdivision into 4 frequency bands

Measurement of rms amplitude in the 4 bands
CTF3 results

Time domain measurements of 4 bands

FFT of down-converted signals

Figure 5: Signal amplitudes from the 4 selected frequencies as a function of the phase in Klystron 15.

Figure 6: Bunch length measurements as a function of the phase of Klystron 15.
Another example (DESY) based on optical radiation

1. The polychromator enables to get the spectrum directly by a single shot. The radiation is deflected by a grating and resolved by a multi-channels detector array

T. Wanatabe et al., NIM-A 480 (2002) 315-327
H. Delsim-Hashemi et al., Proc. FLS, Hamburg 2006, WG512

Slide taken from T.Lefevre (CERN)
Quantization error

- Here we consider only an ideal quantization of a continuous signal (no sampling). Quantized signal is an approximation of the input signal; their difference is the quantization noise.

- Used quantities:
  - $A$ – input signal amplitude
  - $n$ – number of bits
  - $q$ – one bit amplitude:
    \[ q = \frac{2A}{2^n} \]

  - Max quantization error:
    \[ e_m = \frac{\pm q}{2} \]

  - RMS amplitude of the input signal:
    \[ A_{RMS} = \frac{A}{\sqrt{2}} \]

  - Quantisation error RMS amplitude:
    \[ e_{RMS} = \frac{1}{\sqrt{12}} q \approx 0.289 q \]

  - Signal to Noise Ratio:
    \[ SNR = \frac{A_{RMS}}{e_{RMS}} = \frac{\sqrt{6}}{2} \frac{2^n}{2^n} \quad SNR \ [dB] = 20 \log_{10} \frac{\sqrt{6}}{2} 2^n \approx 1.76 + 6.02 \ n \]

  - Effective Number of Bits:
    \[ ENOB = \frac{SNR \ [dB] - 1.76}{6.02} \]
Quantization error

- $N = 10000$ samples of a full scale 4-bit sine
- $f_{in} = 0.01 \times f_s$ (100 samples per $s_{in}$ period)
- 100 samples of 1 period shown, corresponding to 1% of the whole signal

- only one component expected, at $N \times f_{in} / f_s$, that is 100th bin
- Other components have levels in the order of $-40$ dB, that is about 1% of the fundamental
Quantization error and dither

- As before, but added a small noise (blue) to the input signal, of RMS amplitude 0.4 $q$

- Now only one component seen at the expected location
- Noise floor seen at the level in the order of –55 dB, that is about 0.18 % of the fundamental
• So far we looked at the digitization of continuous signals
• Beam signals are different:
  - usually short pulses
  - shape of pulses changes due to beam dynamics
  - good idea is to “look” at these signals with analogue means before using digitized information

• Criteria/buzzwords to design an ADC system:
  - required resolution → number of bits
  - required bandwidth → sampling frequency
  - stability/synchronicity of ADC clock → clock jitter
  - signal level → use full scale of ADC
  - noise contribution: shielding, low impedance signals (low thermal noise)
Sampling a pulse

- 50 mV/div, 2 ns/div
- SPS beam
- 2 pairs of 10 mm button electrodes
- Signals already “filtered” by quite long cables
Single bunch multi pass (circular accelerator)

**Time domain**

\[
f(t) = \sum_{n=1}^{N} A_0 \exp\left(-\frac{(t - nT)^2}{2\sigma_t^2}\right)
\]

\[
\text{area} = \int_{-\infty}^{+\infty} f(t) dt = N \times \sqrt{2\pi} A_0 \sigma_t
\]

**Frequency domain**

\[
F(k) = \sum_{i=1}^{N} F_c(i k_0) \exp\left(-\frac{(k - i k_0)^2}{2\sigma_f^2}\right)
\]

\[
\sigma_f = \frac{1}{2\pi \sigma_t}
\]

\[f_0 = 162.5\text{MHz}\]
• The continuous spectrum of a single bunch passage becomes a line spectrum.

• The line spacing is \( f_{\text{rev}} = 1/T_{\text{rev}} \). (\( T_{\text{rev}} \) = revolution time)

• The amplitude envelope of the line spectrum is the “old” single pass frequency domain envelope of the single bunch.

• Why?
  - short answer: Do the Fourier transform!
  - long answer:
    Understand in more detail 2,3,4...N consecutive bunch passages in time and frequency domain (next slides)
Bunch pattern simulations (1/4)

- Frequencies in this range make a constructive interference (no phase difference)
- Frequencies in this range cancel each other (180° phase difference)
- Other frequencies intermediate summation/cancellation
Bunch pattern simulations (2/4)

\[ \Delta t = 5 \text{ nsec} \]

\[ \Delta t = 10 \text{ nsec} \]

\[ \Delta t = 20 \text{ nsec} \]
Bunch pattern simulations (3/4)

From top to bottom:
3, 5, 10 bunches (0.5nsec long, Δt = 10 nsec)
• 100 equidistant bunches ($\Delta t = 10$ nsec)
• Resulting spectrum is a line spectrum with the fundamental line given by the inverse of the bunch distance
A Measured Longitudinal beam spectrum

• Circular accelerator
  → Beam signal periodic with revolution frequency: \( \omega_{\text{rev}} \)

→ Spectral components at:
  \[
  \omega = n \omega_{\text{rev}}
  \]

Bunch not Gaussian.
Somewhat between triangular and parabolic
Amplitude modulation

Using trigonometric identity:

\[
\begin{align*}
\sin a \sin b &= \frac{1}{2} \cos(a - b) - \cos(a + b) \\
\sin \left(V_{env} \sin 2\pi f_c t\right) &= V_c \sin 2\pi f_c t \\
&= V_c (1 + m \sin 2\pi f_m t) \sin 2\pi f_c t
\end{align*}
\]

\(m =\) modulation index 0...1 \( (V_{env} = V_c) \)
Relevant example of amplitude modulation: stimulated betatron oscillation (or: tune measurement)

Fig. 4: Detecting oscillations using a beam position monitor. The oscillation information is superimposed as a small modulation on a large intensity signal.

Beam centre of charge makes small betatron oscillation around the closed orbit (- stimulated by an exciter or by a beam instability)

Depending on the proximity to an EM sensor the measured signal amplitude varies.

taken from R.Jones, proc. of BI-CAS 2018
Fig. 2: Time and frequency domain representation for a bunch of particles observed at one single location on the circumference of the accelerator. (a & b) continuous measurement without betatron oscillation; (c & d) continuous measurement undergoing betatron oscillation (50% modulation); (e & f) sampled once per revolution.
A measured signal as example

Time domain signal of one beam sensor during betatron oscillation
The same in frequency domain
Multi-bunch multi-pass

• If one has $N$ bunches of equal intensity circulating in an accelerator with $T_{\text{rev}}$ and those bunches only move coherently without any phase difference, then this is undistinguishable from an accelerator with $T_{\text{rev}}/N$ as revolution time and **one bunch** in this accelerator.

• The time domain and frequency domain signals get really mind-boggling, if the bunches start to do individual uncorrelated betatron oscillations.

• The study of these oscillations is important in case of multi-bunch instabilities or in case of the design of transverse active feedback systems.
Multi-bunch modes

Let us consider \( M \) bunches equally spaced around the ring.

Any oscillation pattern of these bunches can be decomposed into a set of eigenmodes of oscillation, the so-called multi-bunch modes.

Each multi-bunch mode is characterized by a bunch-to-bunch phase difference of:

\[
\Delta \Phi = m \frac{2\pi}{M}
\]

\( m = \) multi-bunch mode number \((0, 1, \ldots, M-1)\)

Each multi-bunch eigenmode is characterized by a set of frequencies:

\[
\omega = p M \omega_{rev} \pm (m + \nu) \omega_{rev}
\]

Where:

- \( p \) is an integer number \(-\infty < p < \infty \); \( p=0 \) = baseband
- \( \omega_{rev} \) is the revolution frequency
- \( M\omega_{rev} = \omega_{rep} \) is the bunch repetition frequency
- \( \nu \) is the tune

Hard to understand like this...needs some graphics
Multi-bunch modes: single stable bunch
transverse. One single stable bunch

Every time the bunch passes through the pickup (▼) placed at coordinate 0, a pulse with constant amplitude is generated. If we think it as a Dirac impulse, the spectrum of the pickup signal is a repetition of frequency lines at multiple of the revolution frequency: $p\omega_{\text{rev}}$ for $-\infty < p < \infty$
Multi-bunch modes: single oscillating bunch

One single unstable bunch oscillating at the tune frequency $\nu \omega_0$: for simplicity we consider a vertical tune $\nu < 1$, ex. $\nu = 0.25$. \( M = 1 \rightarrow \) only mode #0 exists

The pickup signal is a sequence of pulses modulated in amplitude with frequency $\nu \omega_0$. Two sidebands at $\pm \nu \omega_0$ appear at each of the revolution harmonics.
Multi-bunch modes: 10 stable bunches

Ten identical equally-spaced stable bunches \((M = 10)\)

The spectrum is a repetition of frequency lines at multiples of the bunch repetition frequency:

\[
\omega_{\text{rep}} = 10 \omega_{\text{rev}} \text{ (bunch repetition frequency)}
\]

\[
\ldots \ldots \ldots -3\omega_{\text{rep}} -2\omega_{\text{rep}} -\omega_{\text{rep}} 0 \omega_{\text{rep}} 2\omega_{\text{rep}} 3\omega_{\text{rep}} \ldots \ldots \ldots
\]
Multi-bunch modes: 10 unstable bunches ($m=0$)

Ten identical equally-spaced unstable bunches oscillating at the tune frequency $\nu \omega_0$ ($\nu = 0.25$)

$M = 10 \rightarrow$ there are 10 possible modes of oscillation

Ex.: mode #0 ($m = 0$)  \[ \Delta \Phi = 0 \] all bunches oscillate with the same phase

\[ \Delta \Phi = m \frac{2\pi}{M} \quad m = 0, 1, \ldots, M-1 \]
Multi-bunch modes: 10 unstable bunches \((m=1)\)

Ex.: mode \#1 \((m = 1)\) \(\Delta \Phi = 2\pi/10\) \((\nu = 0.25)\)

\[
\omega = p\omega_{\text{rep}} \pm (\nu+1)\omega_{\text{rev}} \quad -\infty < p < \infty
\]
Multi-bunch modes: 10 unstable bunches (m=2)

Ex.: mode #2 \( (m = 2) \) \( \Delta \Phi = \frac{4\pi}{10} \) \( (\nu = 0.25) \)

\[ \omega = p\omega_{\text{rep}} \pm (\nu+2)\omega_{\text{rev}} \quad -\infty < p < \infty \]
Multi-bunch modes: 10 unstable bunches (m=3)

Ex.: mode #3 \((m = 3)\) \(\Delta \Phi = 6\pi/10 \ (\nu = 0.25)\)

\[ \omega = p \omega_{rep} \pm (\nu+3)\omega_{rev} \quad -\infty < p < \infty \]
Multi-bunch modes: 10 unstable bunches (m=5)

Ex.: mode #5 (m = 5) $\Delta\Phi = \pi$  ($\nu = 0.25$)

$\omega = p\omega_{\text{rep}} \pm (\nu+5)\omega_{\text{rev}}$  $-\infty < p < \infty$

Aliasing!!!
Multi-bunch modes: 10 unstable bunches \((m=6)\)

Ex.: mode \#6 \((m = 6)\) \(\Delta \Phi = 12\pi/10\) \((\nu = 0.25)\)

\[
\omega = p\omega_{rf} \pm (\nu+6)\omega_0 \quad -\infty < p < \infty
\]
Multi-bunch modes: summary (10 bunches)

If the bunches have not the same charge, i.e., the buckets are not equally filled (uneven filling), the spectrum has frequency components also at the revolution harmonics (multiples of $\omega_{\text{rev}}$). The amplitude of each revolution harmonic depends on the filling pattern of one machine turn.

$$\omega = p M \omega_{\text{rev}} \pm (m + q) \omega_{\text{rev}}$$

Lower sidebands of first revolution harmonics
Multi-bunch modes: coupled-bunch instability

One multi-bunch mode can become unstable if one of its sidebands overlaps, for example, with the frequency response of a cavity high order mode (HOM). The HOM couples with the sideband giving rise to a coupled-bunch instability, with consequent increase of the sideband amplitude.

Effects of coupled-bunch instabilities:
- Increase of the transverse beam dimensions
- Increase of the effective emittance
- Beam loss and max current limitation
- Increase of lifetime due to decreased Touschek scattering (dilution of particles)
Real example of multi-bunch modes

ELETTRA Synchrotron: $f_{\text{rf}}=499.654$ Mhz, bunch spacing $\approx 2$ns, 432 bunches, $f_0 = 1.15$ MHz

$v_{\text{hor}} = 12.30$ (fractional tune frequency $=345$kHz), $v_{\text{vert}} = 8.17$ (fractional tune frequency $=200$kHz)

$v_{\text{long}} = 0.0076$ (8.8 kHz)

$$\omega = p M \omega_0 \pm (m+n) \omega_0$$

Spectral line at 512.185 MHz
Lower sideband of $2f_{\text{rf}}$, 200 kHz apart from the 443$^{\text{rd}}$ revolution harmonic

$\rightarrow$ vertical mode #413

Spectral line at 604.914 MHz
Upper sideband of $f_{\text{rf}}$, 8.8kHz apart from the 523$^{\text{rd}}$ revolution harmonic

$\rightarrow$ longitudinal mode #91
Part II

- Fourier transform of time sampled signals
  a) basics
  b) aliasing
  c) windowing

- Methods to improve the frequency resolution
  a) interpolation
  b) fitting (the NAFF algorithm)
  c) influence of signal to noise ratio

- Analysis of non stationary spectra:
  - STFT (:= Short time Fourrier transform) (Gabor transform)
    also called: Sliding FFT, Spectogram
  - wavelet analysis
  - PLL tune tracking
Discrete Fourier Transform basics

In general:

We use DFTs of $N$ equidistant time sampled signals;

A FFT (Fast Fourier transform) is a DFT with $N = 2^k$.

<table>
<thead>
<tr>
<th>Time Duration</th>
<th>Finite</th>
<th>Infinite</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\omega_k n}$</td>
<td>$X(\omega) = \sum_{n=-\infty}^{+\infty} x(n)e^{-j\omega n}$</td>
<td>discret.</td>
</tr>
<tr>
<td>$k = 0, 1, \ldots, N - 1$</td>
<td>$\omega \in (-\pi, +\pi)$</td>
<td>time</td>
</tr>
<tr>
<td>$X(k) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega_k t} dt$</td>
<td>$X(\omega) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega t} dt$</td>
<td>cont.</td>
</tr>
<tr>
<td>$k = -\infty, \ldots, +\infty$</td>
<td>$\omega \in (-\infty, +\infty)$</td>
<td>$t$</td>
</tr>
<tr>
<td>discrete freq. $k$</td>
<td>continuous freq. $\omega$</td>
<td></td>
</tr>
</tbody>
</table>

**Sampling rate (samples/sec)** $\quad F_s = 1/\Delta t$

**Frame Size (seconds)** $\quad T = N \Delta t$

**Block Size (# samples)** $\quad N$

**Bandwidth or Max Freq (Hz)** $\quad F_{\text{max}} = F_s/2$

**Frequency Resolution (Hz)** $\quad \Delta f = F_{\text{max}}/SL$

**Spectral Lines (# samples)** $\quad SL = N/2$
DFT - aliasing

- Periodic signals, which are sampled with at least 2 samples per period, can be unambiguously reconstructed from the frequency spectrum. (Nyquist-Shannon Theorem)
- In other words, with a DFT one only obtains useful information up to half the sampling frequency.
- Antialiasing filters before the sampling suppress usually unwanted higher spectral information.
Spectral leakage caused by windowing

By measuring a continuous signal only over a finite length, we apply a “data window” to signal, which leads to spectral artefacts in frequency domain.
Windowing = Convolution of continuous signal with window function

- Recall: The Fourier transform of a product in time domain is the convolution of the individual Fourier transforms in Frequency domain.
Rectangular window example

\[ \text{signal} = \text{amp1} \times \sin(2\pi \omega_1 t) + \text{amp2} \times \sin(2\pi \omega_2 t) \]

\[ \text{amp1} = 1 \]
\[ \text{amp2} = 0.01 \]
\[ \omega_1 = 2\pi \times 9990 \text{ Hz} \]
\[ \omega_2 = 2\pi \times 10010 \text{ Hz} \]

The small signal component is completely masked by the sidelobe of the large signal.
Applying the Blackman-Harris window

signal = window * amp1 * sin (2π ω₁t) + amp2 * sin(2π ω₂t)

**Blackman–Harris window**

A generalization of the Hamming family, produced by adding more shifted sinc functions, meant to minimize side-lobe levels

\[ w[n] = a_0 - a_1 \cos \left( \frac{2\pi n}{N} \right) + a_2 \cos \left( \frac{4\pi n}{N} \right) - a_3 \cos \left( \frac{6\pi n}{N} \right) \]

\[ a_0 = 0.35875; \quad a_1 = 0.48829; \quad a_2 = 0.14128; \quad a_3 = 0.01168. \]

The small signal component is nicely resolved
Popular window functions

- The following link contains many frequently used window functions, their main features and application:
- [https://en.wikipedia.org/wiki/Window_function](https://en.wikipedia.org/wiki/Window_function)

The actual choice of the window depends on:
- The signal composition
- The required dynamic range
- The signal to noise ratio

remark: every window except the rectangular window is linked to a loss in amplitude (we multiply many samples with almost “zero”) → reduced S/N up to 6 dB
Improving the frequency resolution of a DFT spectrum

• Recall: basic frequency resolution:
  \[ \Delta f = \frac{2 \cdot f_{\text{samp}}}{N_{\text{samp}}} \]

• We can interpolate between the frequency bin with maximum content and the left and right neighbouring bins

• We limit the discussion to “three point interpolation methods”

• The interpolation function is either:
  A) a parabola of the measurements (:= parabolic interpolation)
  B) a parabola of the log of the measurements (:= Gaussian interpolation)

• Can get up to \(1/N^2\) resolution

Improving the frequency resolution of a DFT spectrum

Table 1. Efficiency of the parabolic and Gaussian interpolation with different windowing methods. The windows are characterised by main lobe width, highest sidelobe level and sidelobe asymptotic fall-off. The maximum interpolation error is given as a percentage of the spectrum bin spacing $\Delta f$. The interpolation gain factor $G$ is defined in (19). Some details concerning the windows and the interpolation errors are given in the Appendix.

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<tr>
<td></td>
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<td></td>
<td></td>
<td>Error max. [% of $\Delta f$]</td>
<td>Gain factor $G$</td>
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<tr>
<td>Rectangular</td>
<td>2</td>
<td>-13.3</td>
<td>6</td>
<td>23.4</td>
<td>2.14</td>
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<tr>
<td>Triangular</td>
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<td>-26.5</td>
<td>12</td>
<td>6.92</td>
<td>7.23</td>
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<td>Hann</td>
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<td>Hamming</td>
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<td>6.80</td>
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<td>Blackman</td>
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<td>6</td>
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<td>10.7</td>
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<tr>
<td>Blackman-Harris</td>
<td>6.54</td>
<td>-74.4</td>
<td>6</td>
<td>4.18</td>
<td>12.0</td>
</tr>
<tr>
<td>Nuttall</td>
<td>8</td>
<td>-98.2</td>
<td>6</td>
<td>3.51</td>
<td>14.2</td>
</tr>
<tr>
<td>Blackman-Harris-Nuttall</td>
<td>8</td>
<td>-93.3</td>
<td>18</td>
<td>3.34</td>
<td>15.0</td>
</tr>
<tr>
<td>Gaussian $L = 6 \sigma$</td>
<td>6.96</td>
<td>-57.2</td>
<td>6</td>
<td>4.95</td>
<td>10.1</td>
</tr>
<tr>
<td>Gaussian $L = 7 \sigma$</td>
<td>10.46</td>
<td>-71.0</td>
<td>6</td>
<td>3.80</td>
<td>13.2</td>
</tr>
<tr>
<td>Gaussian $L = 8 \sigma$</td>
<td>11.41</td>
<td>-87.6</td>
<td>6</td>
<td>2.95</td>
<td>17.0</td>
</tr>
</tbody>
</table>

$$Gain \ factor \ G := \frac{\Delta f}{2 \times Error \ max.}$$

1. Assume a model function for the data (sample $1\ldots N$) (i.e. in the most simple case a monochromatic sin wave), in general $\text{sample}_i = f (i \ast \Delta t)$

2. Get frequency and peak (or interpolated peak) from FFT: $f_{\text{max}}$ and $a_{\text{max}}$

3. Minimize:
   \[
   \Sigma = \sum_{i=0}^{N} (\text{sample}_i)^2 - (a_{\text{max}} \ast \sin (2\pi f_{\text{max}} \ast \Delta t))^2
   \]
   by varying $a_{\text{max}}$ and $f_{\text{max}}$

   (**NAFF algorithm:** Numerical Analysis of Fundamental Frequencies
   → NAFF algorithm can get up to $1/N^4$ resolution)

4. Very good convergence for **noise free data** (i.e. predominantly in simulations)
A little summary on frequency resolution

- Frequency measurement error $\epsilon(N)$ as function of $\log(N)$ for different S/N ratios.
- Basic FFT resolution proportional to $1/N$.
- Plot shows result for interpolation using Hanning window.
- With interpolation and no noise proportional to $1/N^2$.
- Data fitting (NAFF algorithm) also very sensitive to S/N.

A recent development: MultiBPM analysis

Refined betatron tune measurements by mixing BPM data

Basic idea: Create additional samples per turn by using data from neighbouring BPMs (up to 500 in the LHC) and transforming them from samples in space to samples in time.

FIG. 1. A hypothetical ring with eight BPMs at longitudinal positions which are marked with red circles. When the mixed BPM method is employed, a sampling error $\delta_k$ is introduced, due to the deviation of the BPM positions from hypothetical locations that divide the circumference of the ring in exactly eight equal parts, marked with blue circles. BPM 1 is set as the reference point.
During the injection process into the CERN PS strong orbit deflectors are activated. In addition to the wanted orbit change this leads also to an unwanted tune change: Needs to be measured

- Single BPM measurements do not have enough time resolution at high frequency resolution

→ use several BPMs

With remarkable resolution for 40 turns

FIG. 20. Instantaneous betatron tune measurements with the mixed BPM method, during the injection process at the PS. The estimation of the horizontal tunes is shown in thick lines and of the vertical tunes in dashed lines. The analysis is performed for four bunches (bunch 1 in magenta, bunch 2 in red, bunch 3 in green, and bunch 4 in blue) by using a sliding window of 40 turns.
Special case: no spectral leakage

Fig. 1-1. Signal $s(t)$ (black solid line) of unitary amplitude contains two sinusoidal components: the component of interest, $s_{in}(t)$ (red dashed line), whose frequency is to be measured, and an undesirable component, $s_{bg}(t)$ (blue dashed line), considered as a simplified background. Component frequencies are $f_{in} = 100.25$ kHz and $f_{bg} = 110.0$ kHz, their amplitudes $A_{in} = 0.25$ and $A_{bg} = 0.75$.

All pictures: M.Gasior

Fig. 1-3. The magnitude spectrum of $N=1024$ samples of the example signal shown in Fig. 1-2. The smaller spectral peak corresponds to the input component and the bigger to the background one. The input component peak is biased by the spectral leakage effect, while the background peak is narrow and biased only by the spectral leakage of the input component. The right vertical axis is scaled in dB with respect to the highest peak.

The FFT of the so called background signal has no spectral leakage!!!!
Special case continued:

• In the shown example the following relation holds:

$$\frac{f_{\text{background}}}{f_{\text{sampling}}} = \frac{110}{1024} = \frac{M}{N}$$ (ratio of rational numbers)

• This means that with the 1024 samples exactly 110 full periods of the background signals have been measured.

• The mathematical equivalent is that we have not applied a window function (no truncation), we get as result of the FFT the pure sine wave corresponding to the background frequency.

• In accelerators we often know the frequency of a signal for which we want to measure the amplitude (=multiple of RF frequency) → we can avoid spectral leakage.

• Simplest application IQ-sampling at 4*f (next slide)
I-Q Sampling

- Vector representation of sinusoidal signals:
  - Phasor rotating counter-clockwise (pos. freq.)

\[
y(t) = A \sin(\omega t + \varphi_0)
\]

\[
y(t) = A \cos \varphi_0 \sin \omega t + A \sin \varphi_0 \cos \omega t
\]

\[
= : I
\]
\[
= : Q
\]

I: in-phase component
Q: quadrature-phase component

- I-Q sampling at: \( f_s = 4f \)

\[
y(t) = 1.33 \sin(2\pi + \pi / 5)
\]
1. Excite beams with a sinusoidal carrier

2. Measure beam response

3. Sweep excitation frequency slowly through beam response

Other method: Network analysis
Analysis of non-stationary spectra

• Stationary Signal
  – Signals with frequency content unchanged in time
  – All frequency components exist at all times

→ ideal situation for Fourier transform (FT)
  ( orthonormal base functions of Fourier transform are infinitely long, no time information when spectral component happens)

• Non-stationary Signal
  – Frequency composition changes in time

→ need different analysis tools

  – One example: the “Chirp Signal”
Example of simple stationary or non-stationary signals

2 Hz + 10 Hz + 20Hz

Stationary

0.0-0.4: 20 Hz + 0.4-0.7: 10 Hz + 0.7-1.0: 2 Hz

Non-Stationary

CAS 2019 H.Schmickler
linear chirp: 2 Hz to 20 Hz

linear chirp: 20 Hz to 2 Hz

**Upward or downward chirp**

Different in Time Domain

Same in Frequency Domain

At what time a frequency component occurs? FT can not tell!
In order to analyze small section of a signal, Denis Gabor (1946), developed a technique, based on the FT and using *windowing*:

**Short Time Fourier Transform:** STFT

- A compromise between *time-based* and *frequency-based* views of a signal.
- Both time and frequency are represented in *limited precision*.
- The precision is determined by the *size of the window*.
- Once you choose a particular size for the time window - it will be the *same for all frequencies*.
To follow betatron tunes during machine transitions we need time resolved measurements. Simplest example:

- repeated FFT spectra as before (spectrograms)
A very useful form of displaying the result of a STFT is a spectrogram, i.e. a 3D view of many consecutive Fourier transforms, which “slide” along the time series of data. 

**Not bad**, but often we wish a more flexible approach between time and frequencies: solution: wavelet analysis
What is Wavelet Analysis?

And…what is a wavelet…?

A wavelet is a waveform of effectively **limited duration** that has an **average value of zero**.

In a Fourier transform (FT) we represent the data by the **weighted sum of infinite sine waves** with different frequencies.

In the continuous wavelet transform (CWT) we represent the data by the **weighted sum of appropriately scaled and shifted wavelets**.

**Signal**

**Wavelet**

**Transform**

**Constituent wavelets of different scales and positions**
Wavelet Scaling

- Time stretching or frequency scaling:

\[ f(t) = \Psi(t) ; \quad a = 1 \]

Replace \( a \) by \( s \)

\[ f(t) = \Psi(2t) ; \quad a = \frac{1}{2} \]

\[ f(t) = \Psi(4t) ; \quad a = \frac{1}{4} \]
Wavelet Shifting

Moving the wavelet in time:

\[ f(t) \quad | \quad \psi(t) \quad \psi(t-k) \quad \psi(t-2k) \quad \psi(t-3k) \]

Shifting

Scaling
Historical Development of wavelet transforms (main contributors)

• Pre-1930
  – Joseph Fourier (1807) with his theories of frequency analysis

• The 1930s
  – Using scale-varying basis functions; computing the energy of a function

• 1960-1980
  – Guido Weiss and Ronald R. Coifman; Grossman and Morlet

• Post-1980
  – Stephane Mallat; Y. Meyer; Ingrid Daubechies; wavelet applications today
CONTINUOUS WAVELET TRANSFORM (CWT)

\[
\text{CWT}_x^\psi (\tau, s) = \Psi_x^\psi (\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) \cdot \psi^*(\frac{t - \tau}{s}) dt
\]

Translation
(The location of the window)

Scale

Mother Wavelet

Remember Fourier transform:

\[
F(w) = \int_{-\infty}^{\infty} f(t) e^{-iwt} dt
\]

- CWT can be considered as the two-dimensional equivalent to FT.
- The mother wavelets replace the sin/cos functions.
- The scaling of the mother wavelets gives the frequency resolution, the shifting the time resolution.
- There is a large number of different Mother wavelets with different properties.
Computation of CWT

\[
\text{CWT}_x^\psi (\tau, s) = \Psi_x^\psi (\tau, s) = \frac{1}{\sqrt{s}} \int x(t) \cdot \psi^* \left( \frac{t - \tau}{s} \right) dt
\]

Step 1: The wavelet is placed at the beginning of the signal, and set \( s=1 \) (the most compressed wavelet);
Step 2: The wavelet function at scale “1” is multiplied by the signal, and integrated over all times; then multiplied by \( \cdot \);
Step 3: Shift the wavelet to \( t= \), and get the transform value at \( t= \) and \( s=1 \);
Step 4: Repeat the procedure until the wavelet reaches the end of the signal;
Step 5: Scale \( s \) is increased by a sufficiently small value, the above procedure is repeated for all \( s \);
Step 6: Each computation for a given \( s \) fills the single row of the time-scale plane;
Step 7: CWT is obtained if all \( s \) are calculated.
**Time & Frequency Resolution of CWT**

- **Better time resolution; Poor frequency resolution**

- **Better frequency resolution; Poor time resolution**
COMPARISON in terms of time and frequency resolution

From http://www.cerm.unifi.it/EUcourse2001/Gunther_lecturenotes.pdf, p.10
Taken from: Linda Hemmer et al: A putatively novel form of spontaneous coordination

https://www.researchgate.net/publication/23937782, (concerns neural activities)
Which tool to use?

• Stationary Signals:
  windowed FFT with interpolation/fitting.
  !!! Depending on the S/N the gain from very sophisticated methods needs to be evaluated!!!

• Time varying Signals:
  - Good S/N + lots of data: STFT (spectrograms)
    i.e. most of the accelerator applications
  - Small S/N + few data: wavelets
    possible case: instabilities at threshold

• Alternativly (if not complete spectral information is required): PLL tune tracking → next slides
1. So far all methods use exclusively the amplitude information (in the case of self excited oscillations this is the only way)

2. But if you drive through an external force for example a betatron oscillation, you can use the phase between the exciter and the beam response as observable

recall: Network analysis (BTF:=Beam transfer function)
Principle of PLL tune measurements

Due to \( \cos (\varphi) = 0 \) at resonance this system “looks” to the 90 deg. point of the BTF

Recall: \( \sin a \sin b = \frac{1}{2} (\cos(a - b) - \cos(a + b)) \)

Beam

BPM
\( B \sin(\omega t + \varphi) \)

Phase detector (=product)
\( \frac{1}{2}AB\cos(\varphi) - \cos(2\omega t + \varphi) \)

Lowpass

Frequency control:
\( \frac{1}{2}AB\cos(\varphi) \)

VCO
Voltage controlled oscillator
\( A \sin(\omega t) \)

Control system can read tune betatron tune at regular intervals by reading the VCO frequency

VCO changes \( \omega \) until control input == 0
Illustration of PLL tune tracking

Single carrier PLL locks on 90° point of BTF;
Q’ Measurement via RF-frequency modulation (momentum modulation)

Applied Frequency Shift
Δ F (RF)

Amplitude & sign of chromaticity calculated from continuous tune plot
Measurement example during changes on very strong quadrupoles in the insertion: LEP $\beta$-squeeze
Summary

• Single beam passage in a detector produces a signal with a continuous frequency spectrum. The shorter the bunch, the higher the frequency content.
• Repetitive bunch passages produce a line spectrum. They are called revolution harmonics.

Details of the bunch pattern, differences in bunch intensities etc. determine the final spectral distribution.
• Transverse or longitudinal oscillations of the bunch around the equilibrium produce sidebands around all revolution harmonics.
• These sidebands are used for the measurement of the betatron tunes or the synchrotron tune.

• The standard tool for obtaining spectral information is a Fourier transform (FFT) of the time sampled signals.
• Windowing and interpolation allow higher resolution measurements.
• Spectograms or STFTs are consecutive FFTs of larger datasets, which allow to follow time varying spectra.
• Wavelet diagrams are an alternative analysis tool.
• Phase locked loops can be used for continuous tune tracking.
Appendix I: Python Code for bunch pattern display
import numpy as np
from numpy import fft
import matplotlib.pyplot as plt

N=16384
NBUNCH=100
sigmax = 0.5

deltax=10
T=1/N
NLEFT=-50
NRIGHT=50

x1= np.linspace(NLEFT,N-NLEFT,N)
xtime=np.linspace(NLEFT, NBUNCH*deltax + NRIGHT,N)
IB=0
y=NBUNCH*np.exp(-x1*x1)/(2*sigmax*sigmax))
ytime=NBUNCH*np.exp(-(xtime*xtime)/(2*sigmax*sigmax))
y1=0
y2=0
y3=0
ytime=0

while True:

    y1=y1+np.exp(-(x1-IB*deltax)*(x1-IB*deltax)/(2*sigmax*sigmax))
ytime=ytime+np.exp(-(xtime-IB*deltax)*(xtime-IB*deltax)/(2*sigmax*sigmax))
IB=IB+1
if IB==NBUNCH:
    break
Appendix Ib: Python code for bunch pattern simulation 2\textsuperscript{nd} part

• \texttt{fft=(fft.fft(y))}
• \texttt{fft1=(fft.fft(y1))}
• \texttt{x2=np.linspace(0.0,500,N/2)}
• \texttt{y2=2.0*np.abs(fft1[:N//2])/float(N)}
• \texttt{y3=2.0*np.abs(fft[:N//2])/float(N)}

• \texttt{plt.rcParams["figure.figsize"] = [15,4]}
• \texttt{plt.subplot(1,2,1)}

• \texttt{plt.plot(xtime,ytime,'b-')}
• \texttt{plt.ylabel('amplitude')}
• \texttt{plt.xlabel('time [nsec]')}

• \texttt{plt.subplot(1,2,2)}

• \texttt{plt.plot(x2,y3,'r-')}
• \texttt{plt.plot(x2,y2,'b-')}
• \texttt{plt.ylabel('amplitude')}
• \texttt{plt.xlabel('frequency [MHz]')}

• \texttt{plt.tight_layout()}
• \texttt{plt.savefig('whatever.png')}
• \texttt{plt.show()}