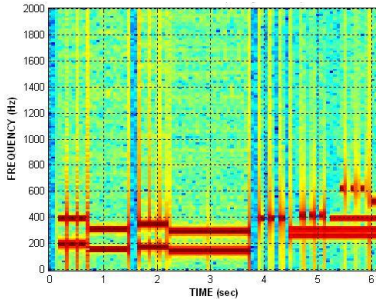


COMS20017 – Algorithms & Data

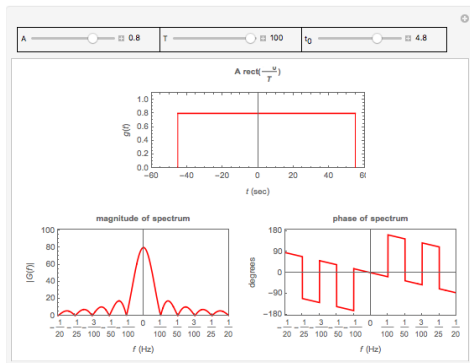


March 2025
1D Fourier Transform

Majid Mirmehdi

Lecture MM-05

Next in DDCS



Feature Selection and Extraction

- Signal basics
- **1D Fourier Transform**
- Another look at features
- PCA for dimensionality reduction
- Convolutions

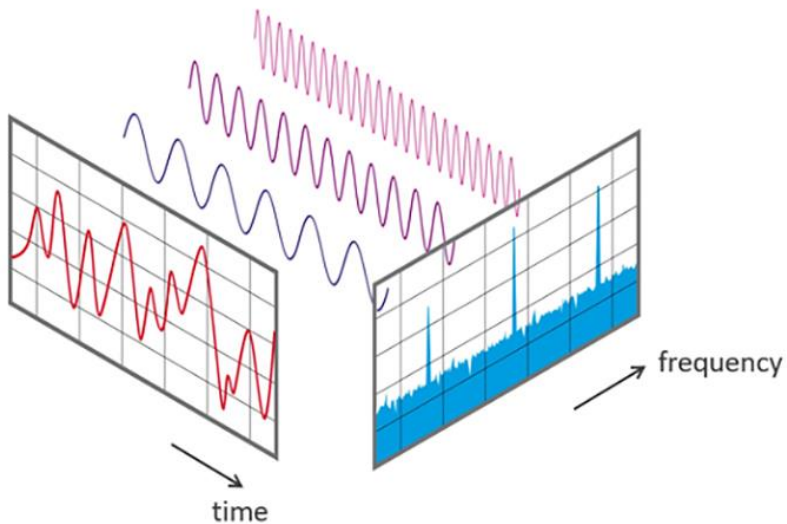
Frequency Analysis for Feature Extraction & more...

- The aim of processing a signal using Fourier analysis is to *manipulate the spectrum of a signal* rather than manipulating the signal itself. Example: *simple compression*



- Functions that are **not periodic** can also be expressed as the integral of sines and/or cosines weighted by a coefficient, using the **Fourier transform**.

Visualising the outcome of the FT



1D Fourier Transform

The Fourier Transform of a single variable continuous function $f(x)$ is:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux} dx$$

Conversely, given $F(u)$, we can obtain $f(x)$ by means of the *inverse* Fourier Transform:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux} du$$

These two equations are also known as the Fourier Transform Pair.

Note, they constitute a lossless representation of data.

1D Fourier Transform: discrete form

The Fourier Transform of a discrete function of one variable, $f(x)$, $x=0,1,2\dots,N-1$ is:

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{\frac{-j2\pi ux}{N}} \quad \text{for } u = 0,1,2,\dots,N-1.$$

Conversely, given $F(u)$, we can obtain $f(x)$ by means of the *inverse* Fourier Transform:

$$f(x) = \sum_{u=0}^{N-1} F(u) e^{\frac{j2\pi ux}{N}} \quad \text{for } x = 0,1,2,\dots,N-1.$$

These two equations are also known as the Fourier Transform Pair.

Note, they constitute a lossless representation of data.

1D Fourier Transform

The concept of the frequency domain follows from *Euler's Formula*:

$$e^{-j\theta} = \cos \theta - j \sin \theta$$

Thus, each term of the Fourier Transform is composed of the sum of *all* values of the function $f(x)$ multiplied by sines and cosines of various frequencies:

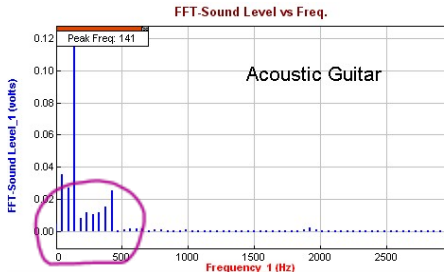
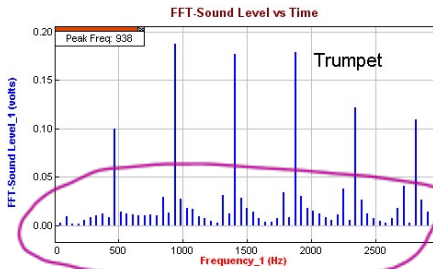
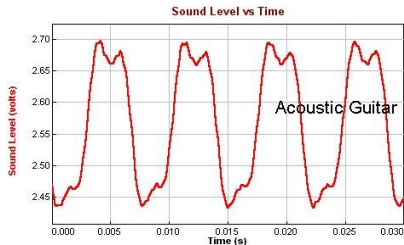
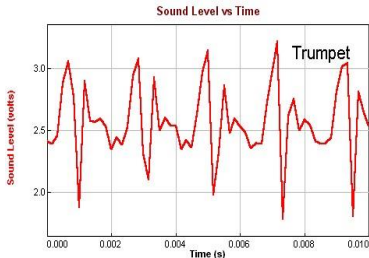
$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) \left[\cos\left(\frac{2\pi ux}{N}\right) - j \sin\left(\frac{2\pi ux}{N}\right) \right]$$

for $u = 0, 1, 2, \dots, N - 1$.

We have transformed from a **time domain** to a **frequency domain** representation.

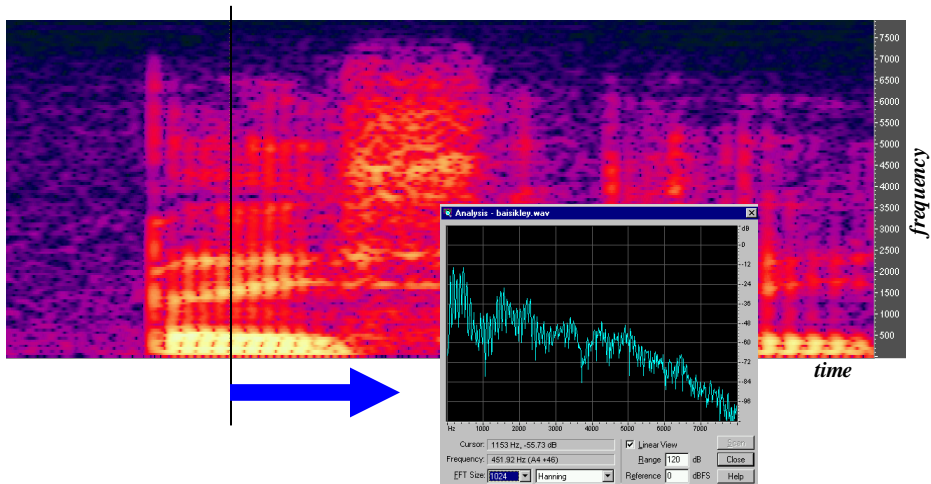
Example: low and high frequencies

Characteristics of sound in audio signals:

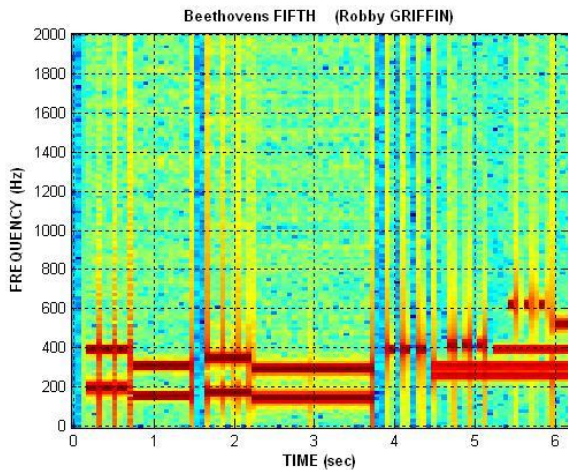


Example: Acoustic Data Analysis

Spectrogram



Can you match the sound to the frequencies?



1D Fourier Transform

$F(u)$ is a complex number & has
real and imaginary parts:

$$F(u) = R(u) + jI(u)$$

Magnitude or *spectrum* of the FT:

$$|F(u)| = \sqrt{R^2(u) + I^2(u)}$$

Phase angle or phase spectrum:

$$\varphi(u) = \tan^{-1} \frac{I(u)}{R(u)}$$

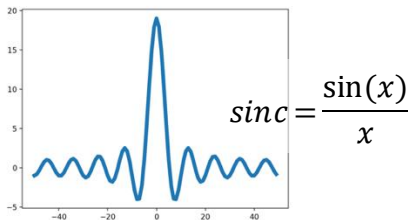
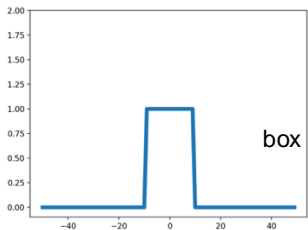
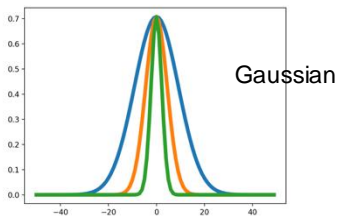
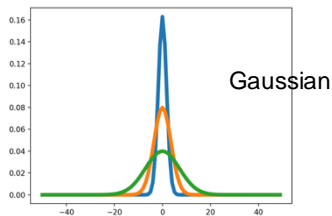
Expressing $F(u)$ in polar coordinates:

$$F(u) = |F(u)|e^{j\varphi(u)}$$

1D Fourier Transform examples

Signal

Fourier
transform



Some Properties of Fourier Transform

Linearity

$$a f(x) + b h(x) \Leftrightarrow a F(u) + b H(u)$$

*Zero-frequency
(DC component)*

$$f(0) \Leftrightarrow \int_{-\infty}^{\infty} f(x) dx$$

Time-shifting

$$f(x - x_0) \Leftrightarrow e^{-j2\pi x_0 u} F(u)$$

Same frequency content, but introduces a phase shift in the frequency domain

Time-scaling

$$f(ax) \Leftrightarrow \frac{1}{|a|} F\left(\frac{u}{a}\right) \quad a \neq 0$$

1D Fourier Transform of box signal (example of time-scaling)

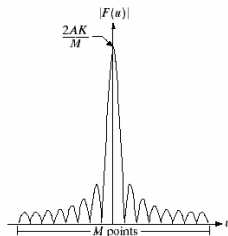
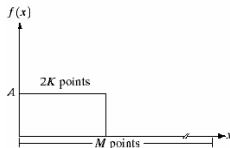
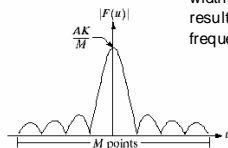
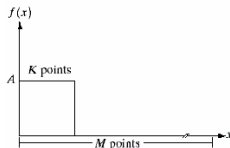
$$f(x) = \begin{cases} 1 & 0 \leq x \leq K \\ 0 & \text{otherwise} \end{cases}$$

The width of the main lobe is inversely proportional to the pulse width K . A wider box signal (larger K) results in a narrower main lobe in the frequency domain, and vice versa.

$$A = 1$$

$$K = 8$$

$$M = 1024$$



$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux} dx$$

$$F(u) = \int_0^K e^{-j2\pi ux} dx$$

$$F(u) = K \left| \frac{\sin(\pi ux)}{\pi ux} \right|$$

The Fourier spectrum of the box signal is a sinc function

The box signal in the time domain has sharp transitions (0 to A and back), which require high-frequency components (infinite sum of sinusoidal components) to represent them accurately in the frequency domain.

Very Simple Application Example

Automatic speech recognition between two speech utterances $x(n)$ and $y(n)$:

Naïve approach:



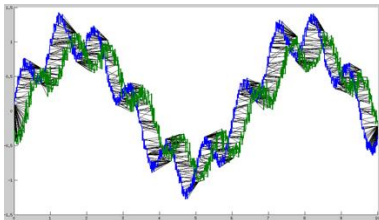
$$E = \sum_{\forall n} (x(n) - y(n))^2$$

Problems with this approach?

$$\left\{ \begin{array}{l} x(n) = K y(n), \text{ yet } E \neq 0 \\ K \text{ being a scaling parameter} \end{array} \right.$$

$$\left\{ \begin{array}{l} x(n) = y(n - m), \text{ yet } E \neq 0 \\ m \text{ causing a delay shift} \end{array} \right.$$

One solution could be Dynamic Time Warping? (recall from earlier lecture)



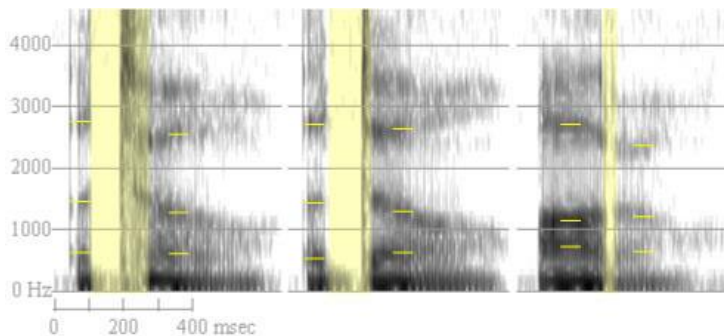
Use Frequency Domain Features!

- Take the Fourier transform of both utterances to get $X(u)$ and $Y(u)$.
- Then consider the Euclidean distance between their magnitude spectrums: $|X(u)|$ and $|Y(u)|$:

$$d_E = \sum_{\forall u} (|X(u)| - |Y(u)|)^2$$

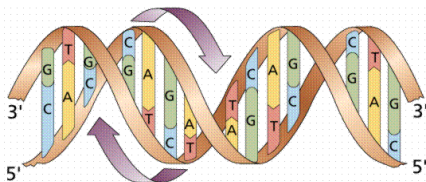
Use Frequency Domain Features!

Still a difficult task even in the frequency domain.



DNA Sequence Example

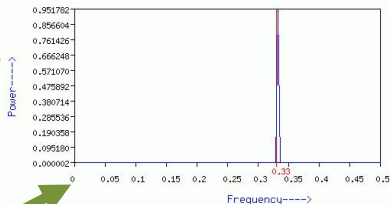
- The analysis of correlations in DNA sequences is used to identify protein coding genes in genomic DNA.
- Locating and characterizing repeats and periodic clusters provides certain information about the structural and functional characteristics of the molecule.
- DNA sequences are represented by letters, **A**, **C**, **G** or **T**, and **-**
- e.g. **ACAATG-GCCATAAT-ATGTGAAC--GCTCA...**



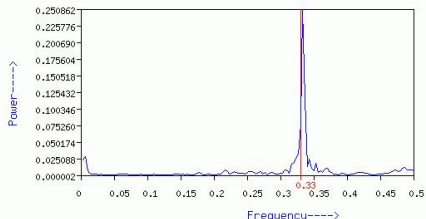
DNA Sequence Example

Consider the periodic sequence **A**--**A**--**A**--**A**--.....
where blanks can be filled randomly by **A**, **C**, **G**
or **T**. This shows a periodicity of 3.

The spectral density of such a sequence is significantly non-zero only at one frequency (0.33) which corresponds to the perfect periodicity of base **A** ($1/0.333 = 3.0$).



Destroy the perfect repetition by randomly replacing the **A**'s with any of the letters...




DNA Sequence Analysis

The computation of Fourier & other linear transforms of *symbolic data* is a big problem.


The simplest solution is to map each symbol to a number.

Consider, for example, the following symbolic periodic sequence:
 $s = (\text{ATAGACATAGACATAGAC} \dots)$.

The mapping:

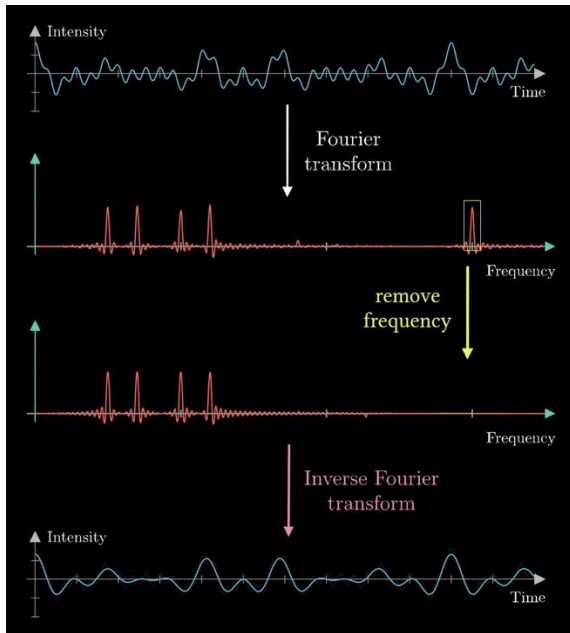
A \rightarrow 1,
T \rightarrow 0,  Period = 2
G \rightarrow 0,
C \rightarrow 0,

The mapping:

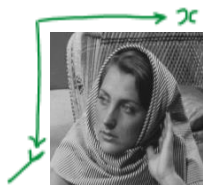
A \rightarrow 1,
T \rightarrow 2,  Period = 6
G \rightarrow 3,
C \rightarrow 4,

This clearly shows that some of the relevant harmonic structure can be exposed by the symbolic-to-numeric labelling.

Another Example: Noise Removal



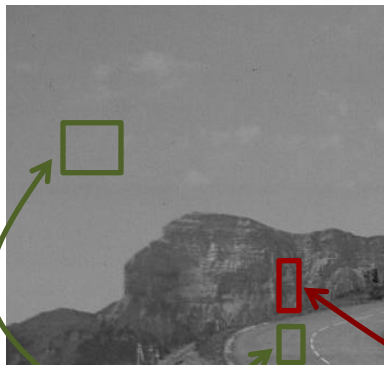
The 2D Fourier Transform (NOT IN EXAM)



FT \rightarrow straightforward extension to 2D:

- Images are functions of two variables \rightarrow e.g. $f(x, y)$
- Defined in terms of *spatial frequency* \rightarrow 2D frequency.
- Fourier Transform is particularly useful for characterising intensity variations across an image.
- FT identifies the *Rate of change of intensity* along each dimension.

Examples: 2D Spatial Frequency (NOT IN EXAM)



Slowly changing \rightarrow low frequency

Rapidly changing \rightarrow high frequency

More on the 2D FT next year in the *Image Processing and Computer Vision* unit

Frequency Spectrum – Summary

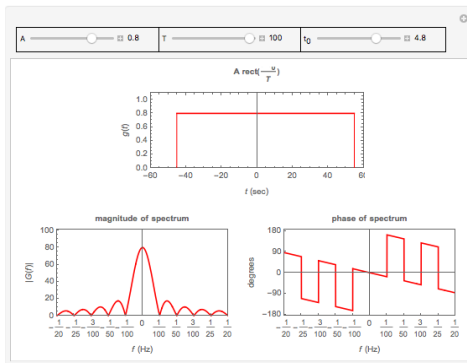
$$|F(u)| = \sqrt{R^2(u) + I^2(u)}$$

- Distribution of $|F(u)| \rightarrow$ frequency spectrum/space of signal.
- Features often extracted from the **Power Spectrum**:

$$\omega(f) = |F(u)|^2$$

- Slowly changing signals \rightarrow spectrum concentrated around low frequencies.
- Rapidly changing signals \rightarrow spectrum concentrated around high frequencies.
- Also bandlimited signals \rightarrow frequency content confined within some frequency band.

Next...



Feature Selection and Extraction

- Signal basics
- 1D Fourier Transform
- **Another look at features**
- PCA for dimensionality reduction
- Convolutions