

# Lecture 5: Short-Time Fourier Transform and Filterbanks

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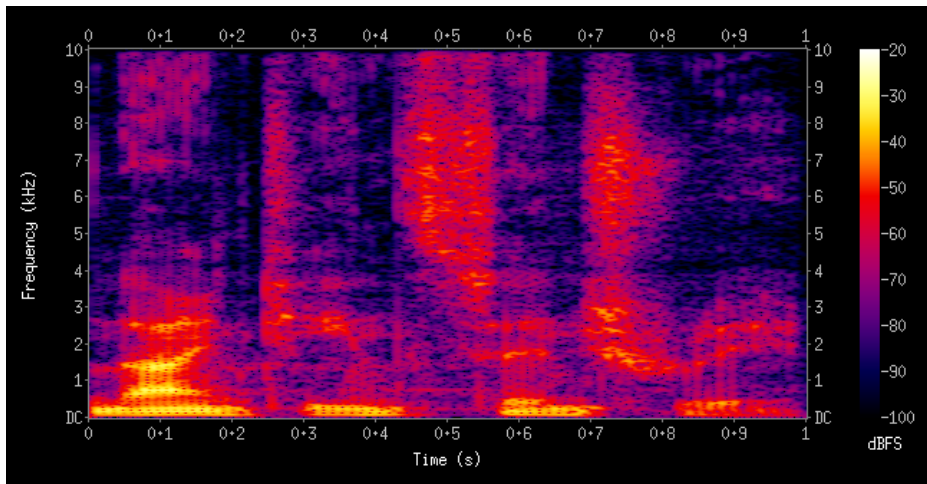
ECE 417: Multimedia Signal Processing, Fall 2023

- 1 Short-Time Fourier Transform
- 2 STFT as a Linear-Frequency Filterbank
- 3 Inverse STFT
- 4 Implementing Nonlinear-Frequency Filterbanks Using the STFT
- 5 Summary

# Outline

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# Spectrogram = $20 \log_{10} |\text{Short Time Fourier Transform}|$



# Short Time Fourier Transform

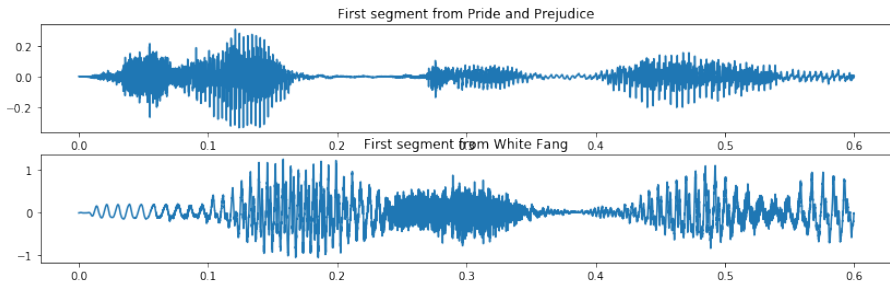
The short-time Fourier Transform (STFT) is the Fourier transform of a short part of the signal. We write either  $X_m(\omega)$  or  $X_m[k]$  to mean:

- The DFT of the short part of the signal that starts at sample  $m$ ,
- windowed by a window of length  $L \leq N$  samples,
- evaluated at frequency  $\omega = \frac{2\pi k}{N}$ .

The next several slides will go through this procedure in detail, then I'll summarize.

# Step #1: Chop out part of the signal

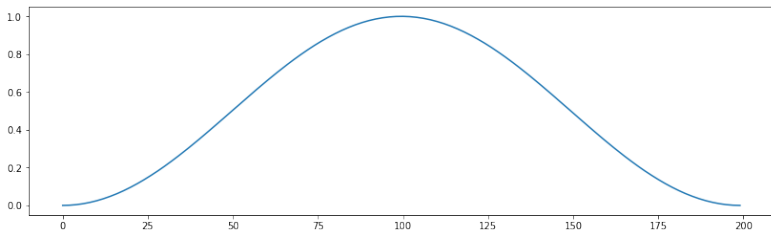
First, we just chop out the part of the signal starting at sample  $m$ . Here are examples from Librivox readings of *White Fang* and *Pride and Prejudice*:



## Step #2: Window the signal

Second, we window the signal. A window with good spectral properties is the Hamming window. The length of the window might be  $L$ , which might be less than the FFT length  $N$ :

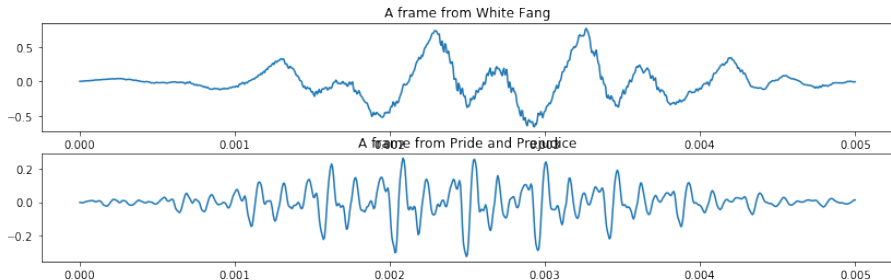
$$w[n] = \begin{cases} 0.54 - 0.46 \cos\left(\frac{2\pi n}{L-1}\right) & 0 \leq n \leq L-1 \\ 0 & \text{otherwise} \end{cases}$$



## Step #2: Window the signal

Here is the windowed signals, which is nonzero for  $0 \leq n - m \leq (L - 1)$ :

$$x[n, m] = w[n - m]x[n]$$



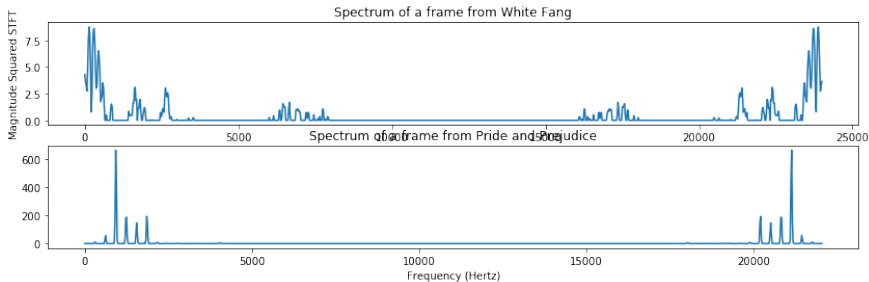


# Step #3: Fourier Transform

Finally, we take the DTFT of the windowed signal. The result is the STFT,  $X_m(\omega)$ :

$$X_m(\omega) = \sum_{n=m}^{m+(L-1)} w[n-m]x[n]e^{-j\omega(n-m)}$$

Here it is, plotted as a function of  $k$ :





# Putting it all together: STFT

The STFT, then, is defined as

$$X_m(\omega) = \sum_n w[n - m]x[n]e^{-j\omega(n-m)}, \quad \omega = \frac{2\pi k}{N}$$

which we can also write as

$$X_m[k] = \text{DFT} \{w[n]x[n + m]\}$$

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# STFT as a bank of analysis filters

The STFT is defined as:

$$X_m[k] = \sum_{n=m}^{m+(L-1)} w[n-m]x[n]e^{-j\omega_k(n-m)}$$

which we can also write as

$$X_m[k] = x[m] * h_k[m]$$

where

$$h_k[m] = w[-m]e^{j\omega_k m}$$

The frequency response of this filter is just the DTFT of  $w[-m]$ , which is  $W(-\omega)$ , shifted up to  $\omega_k$ :

$$H_k(\omega) = W(\omega_k - \omega)$$

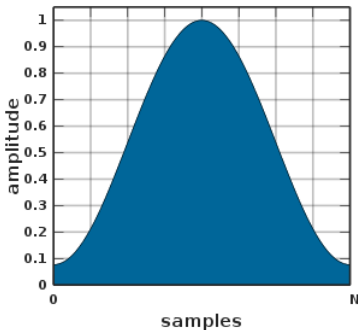
# Hamming window spectrum

The frequency response of this filter is just the DTFT of  $w[-m]$ , which is  $W(-\omega)$ , shifted up to  $\omega_k$ :

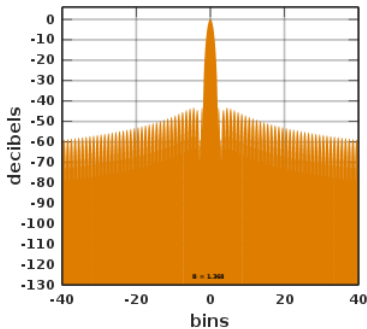
$$H_k(\omega) = W(\omega_k - \omega)$$

For a Hamming window,  $w[n]$  is on the left,  $W(\omega)$  is on the right:

Hamming window ( $a_0 = 0.53836$ )

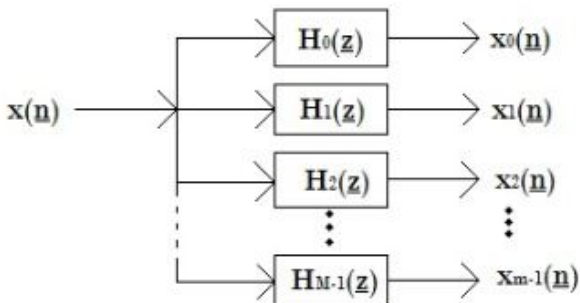


Fourier transform



# STFT as a bank of analysis filters

So the STFT is just like filtering  $x[n]$  through a bank of analysis filters, in which the  $k^{\text{th}}$  filter is a bandpass filter centered at  $\omega_k$ :



## Multidimensional Analysis Filter Banks

By Ventetpluie, GFDL,

[https://en.wikipedia.org/wiki/File:Multidimensional\\_Analysis\\_Filter\\_Banks.jpg](https://en.wikipedia.org/wiki/File:Multidimensional_Analysis_Filter_Banks.jpg)

# Short-Time Fourier Transform

- **STFT as a Transform:**

$$X_m[k] = \text{DFT} \{w[n]x[n + m]\}$$

- **STFT as a Filterbank:**

$$X_m[k] = x[m] * h_k[m], \quad h_k[m] = w[-m]e^{j\omega_k m}$$



# Outline

- ① Short-Time Fourier Transform
- ② STFT as a Linear-Frequency Filterbank
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# Short-Time Fourier Transform

- **STFT as a Transform:**

$$X_m[k] = \text{DFT} \{w[n]x[n + m]\}$$

- **STFT as a Filterbank:**

$$X_m[k] = x[m] * h_k[m], \quad h_k[m] = w[-m]e^{j\omega_k m}$$

# The inverse STFT

STFT as a transform is defined as:

$$X_m[k] = \sum_{n=m}^{m+(N-1)} w[n-m]x[n]e^{-j2\pi k(n-m)/N}$$

Obviously, we can inverse transform as:

$$x[n] = \frac{1}{Nw[n-m]} \sum_{k=0}^{N-1} X_m[k]e^{j2\pi k(n-m)/N}$$

# The inverse STFT

We get a better estimate of  $x[n]$  if we average over all of the windows for which  $w[n - m] \neq 0$ . This is often called the overlap-add method, because we overlap the inverse-transformed windows, and add them together:

$$x[n] = \frac{\sum_m \frac{1}{N} \sum_{k=0}^{N-1} X_m[k] e^{j\omega_k(n-m)}}{\sum_m w[n-m]}$$

Often, the denominator is a constant, independent of  $n$ . That happens automatically if there has been no downsampling; it is

$$W(0) = \sum_{m=0}^{N-1} w[m]$$

# STFT: Forward and Inverse

- **Short Time Fourier Transform (STFT):**

$$X_m[k] = \sum_n w[n - m]x[n]e^{-j\omega_k(n-m)}, \quad \omega_k = \frac{2\pi k}{N}$$

- **Inverse Short Time Fourier Transform (ISTFT, OLA method):**

$$x[n] = \frac{1}{NW(0)} \sum_m \sum_{k=0}^{N-1} X_m[k]e^{j\omega_k(n-m)}$$

# ISTFT as a bank of synthesis filters

**Inverse Short Time Fourier Transform (ISTFT):**

$$x[n] = \frac{1}{NW(0)} \sum_m \sum_{k=0}^{N-1} X_m[k] e^{j\omega_k(n-m)}$$

The ISTFT is the sum of filters:

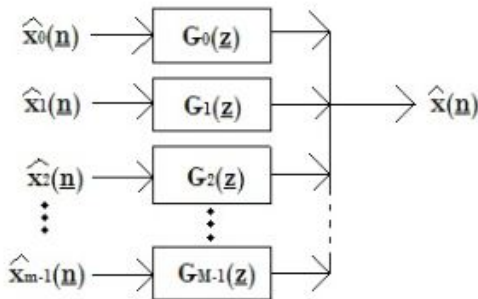
$$\begin{aligned} x[n] &= \frac{1}{W(0)} \sum_m \sum_{k=0}^{N-1} X_m[k] e^{j\omega_k(n-m)} \\ &= \sum_{k=0}^{N-1} (X_m[k] * g_k[m]) \end{aligned}$$

where

$$g_k[m] = \begin{cases} \frac{1}{W(0)} e^{j\omega_k m} & 0 \leq m \leq N-1 \\ 0 & \text{otherwise} \end{cases}$$

# ISTFT as a bank of synthesis filters

So the ISTFT is just like filtering  $X_m[k]$  through a bank of synthesis filters, in which the  $k^{\text{th}}$  filter is a bandpass filter centered at  $\omega_k$ :



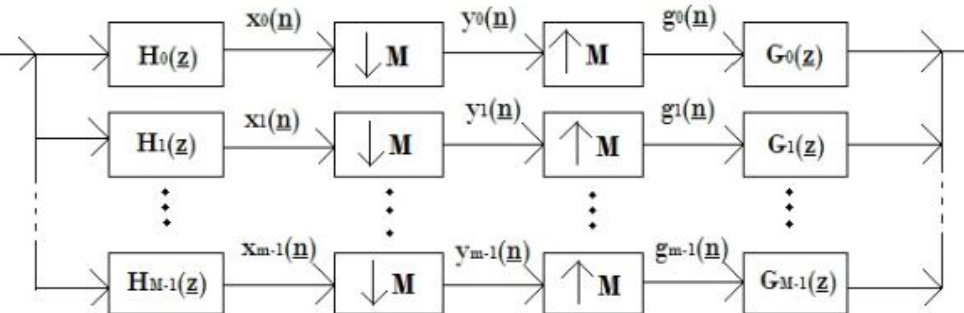
## Multidimensional Synthesis Filter Banks

By Ventetpluie, GFDL,

[https://en.wikipedia.org/wiki/File:Multidimensional\\_Synthesis\\_Filter\\_Banks.jpg](https://en.wikipedia.org/wiki/File:Multidimensional_Synthesis_Filter_Banks.jpg)

# The whole process: STFT and ISTFT as a filterbanks

We can compute the STFT, downsample, do stuff to it, upsample, and then resynthesize the resulting waveform:



**Multidimensional M\_Channel Filter Banks**

By Ventetpluie, GFDL,

[https://en.wikipedia.org/wiki/File:Multidimensional\\_M\\_Channel\\_Filter\\_Banks.jpg](https://en.wikipedia.org/wiki/File:Multidimensional_M_Channel_Filter_Banks.jpg)



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# Short-Time Fourier Transform

- **STFT as a Transform:**

$$X_m[k] = \text{DFT} \{w[n]x[n + m]\}$$

- **STFT as a Filterbank:**

$$X_m[k] = x[m] * h_k[m], \quad h_k[m] = w[-m]e^{j\omega_k m}$$

# Relative Benefits of Transforms vs. Filters

- **STFT as a Transform:** Implement using Fast Fourier Transform.

$$X_m[k] = \text{DFT} \{w[n]x[n + m]\}$$

**Computational Complexity** =  $\mathcal{O} \{N \log_2(N)\}$  per  $m$

**Example:**  $N = 1024$

**Computational Complexity** = 10240 multiplies/sample

- **STFT as a Filterbank:** Implement using convolution.

$$X_m[k] = x[m] * h_k[m]$$

**Computational Complexity** =  $\mathcal{O} \{N^2\}$  per  $m$

**Example:**  $N = 1024$

**Computational Complexity** = 1048576 multiplies/sample

# What about other filters?

- Obviously, FFT is much faster than the convolution approach.
- Can we use the FFT to speed up other types of filter computations, as well?
- For example, can we model the bandpass filtering operations of the human ear from the STFT?

# What about other filters?

- We want to find  $y[n] = f[n] * x[n]$ , where  $f[n]$  is a length- $N$  impulse response.
- Complexity of the convolution in time domain is  $\mathcal{O}\{N\}$  per output sample.
- We can't find  $y[n]$  exactly, but we can find  $\tilde{y}[n] = f[n] \circledast (w[n-m]x[n])$  from the STFT:

$$Y_m[k] = F[k]X_m[k]$$

- It makes sense to do this only if  $F[k]$  has far fewer than  $N$  non-zero terms (narrowband filter).

# Bandpass-Filtered Signal Power

In particular, suppose that  $f[n]$  is a bandpass filter, and we'd like to know how much power gets through it.

So we'd like to know the power of the signal

$\tilde{y}[n] = f[n] \circledast (w[n - m]x[n])$ . We can get that as

$$\begin{aligned} \sum_{n=0}^{N-1} \tilde{y}[n]^2 &= \frac{1}{N} \sum_{k=0}^{N-1} |Y_m[k]|^2 \\ &= \frac{1}{N} \sum_{k=0}^{N-1} |F[k]|^2 |X_m[k]|^2 \end{aligned}$$

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- **STFT as a Transform:**

$$X_m(\omega) = \sum_n w[n-m]x[n]e^{-j\omega(n-m)}, \quad \omega_k = \frac{2\pi k}{N}$$

- **STFT as a Filterbank:**

$$X_m(\omega) = x[m] * h_k[m], \quad h_\omega[m] = w[-m]e^{j\omega m}$$

- **Other filters using STFT:**

$$\text{DFT} \{f[n] \circledast (w[n-m]x[n])\} = H[k]X_m[k]$$

- **Bandpass-Filtered Signal Power**

$$\sum_{n=0}^{N-1} \tilde{y}[n]^2 = \frac{1}{N} \sum_{k=0}^{N-1} |F[k]|^2 |X_m[k]|^2$$