Spectrogram and the STFT

由 Tom Bäckström创建, 最后修改于三月 28, 2019

We have intuitive notion of what a high or low pitch means. Pitch refers to our perception of the frequency of a tonal sound. The Fourier *spectrum* of a signal reveals such frequency content. This makes the spectrum an intuitively pleasing domain to work in, because we can visually examine signals.

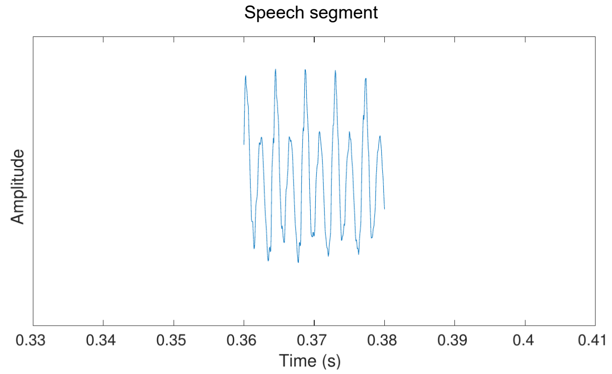
In practice, we work with discrete-time signals, such that the corresponding time-frequency transform is the discrete Fourier transform. It maps a length N signal x_n into a complex valued frequency domain representation X_k of N coefficients as

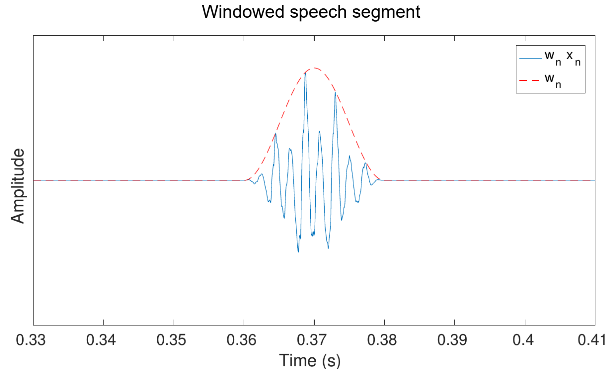
$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi\frac{kn}{N}}.$$

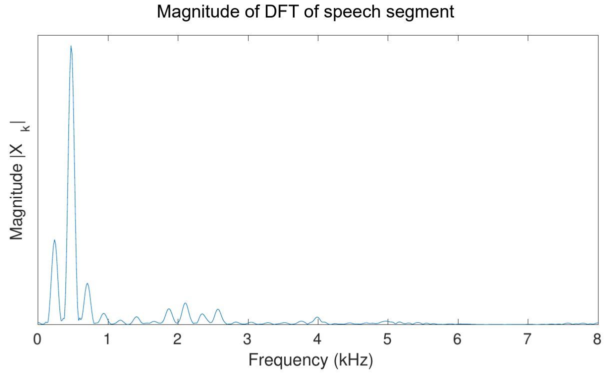
For real-valued inputs, positive and negative frequency components are complex conjugates of each other, such that we retain N unique units of information. However, since spectra are complex-valued vectors, it is difficult to visualize them as such. A first solution would be to plot the magnitude spectrum $|X_k|$ or power spectrum $|X_k|^2$. Due to large differences in the range of different frequencies, unfortunately these representations do not easily show relevant information.

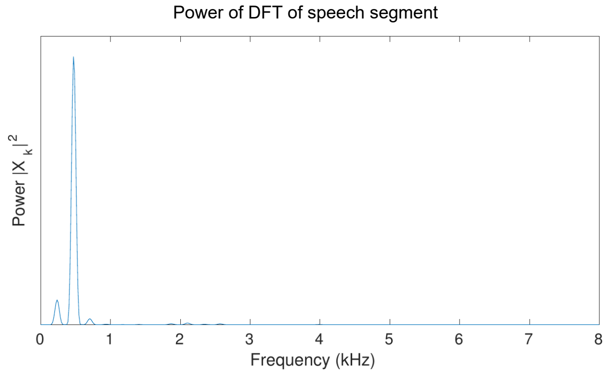
The log-spectrum $20\log_{10}|X_k|$ is the most common visualization of spectra and it gives the spectrum in decibels. It is useful because again, it gives a visualization where sounds can be easily interpreted.

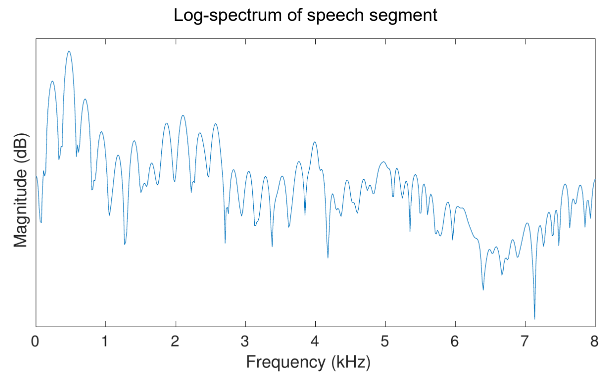
Since Fourier transforms are covered by basic works in signal processing, we will here assume that readers are familiar with the basic properties of these transforms.











Speech signals are however non-stationary signals. If we transform a spoken sentence to the frequency domain, we obtain a spectrum which is an average of all phonemes in the sentence, whereas often we would like to see the spectrum of each individual phoneme separately.

By splitting the signal into shorter segments, we can focus on signal properties at a particular point in time. Such segmentation was already discussed in the *windowing* section.

By windowing and taking the discrete Fourier transform (DFT) of each window, we obtain the *short-time Fourier transform* (STFT) of the signal. Specifically, for an input signal x_n and window w_n, the transform is defined as

$$STFT\{x_n\}(h,k) = X(h,k) = \sum_{n=0}^{N-1} x_{n+h} w_n e^{-i2\pi\frac{kn}{N}}.$$

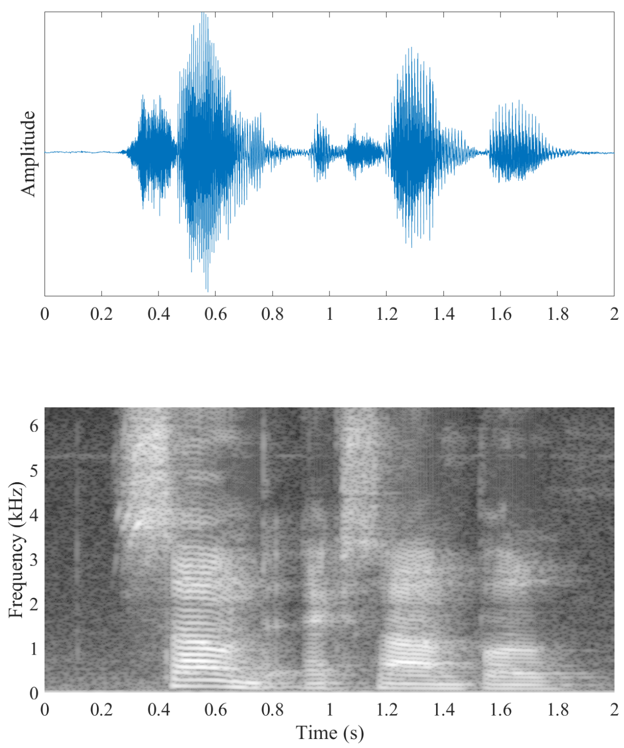
The STFT is one of the most frequently used tools in speech analysis and processing. It describes the evolution of frequency components over time. Like the spectrum itself, one of the benefits of STFTs is that its parameters have a physical and intuitive interpretation.

A further parallel with a spectrum is that the output of the STFT is complex-valued, though where the spectrum is a vector, the STFT output is a matrix. As a consequence, we cannot directly visualize the complex-valued output. Instead, STFTs are usually visualized using their log-spectra, $20\log_{10}(X(h,k))$. Such 2 dimensional log-spectra can then be visualized with a heat-map known as a *spectrogram*.

When looking at speech in a spectrogram, like the figure on the right, depicting a sentence "*Sound Example*", many important features of the signal can be clearly observed:

- Horizontal lines in a comb-structure correspond to the fundamental frequency. For example, in the figure on the right, at 0.5 s there is the vowel /e/ and /a/ at 1.3 s which has clear horizontal lines.
- Vertical lines correspond to abrupt sounds, which are often characterized as transients. Typical transients in speech are stop consonants. In the figure on the right, there is a /d/ at 0.8 s and /ks/ at 1 s.
- Areas which have a lot of energy in the high frequencies (appears as a lighter colour), like at approximately 0.3 s in the figure on the right, correspond to noisy sounds like fricatives. In the figure on the right we can found the /s/ sound at both 0.3 and 1.1 s.

A speech signal and its spectrogram



无标签