

# Bilinear transforms

Henri



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Henri Padé  
1863–1953

## Bilinear transform

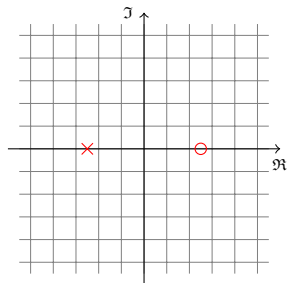
A way of finding a z-transform given a Laplace transform.

$$z = \exp(sT) = \frac{\exp\left(\frac{sT}{2}\right)}{\exp\left(-\frac{sT}{2}\right)} \approx \frac{1 + \frac{sT}{2}}{1 - \frac{sT}{2}}.$$
$$s \approx \frac{2}{T} \frac{z - 1}{z + 1}.$$

i.e.,

$$H(z) = H(s) \Big|_{s = \frac{2}{T} \frac{z-1}{z+1}}$$

## All pass filter, s-plane

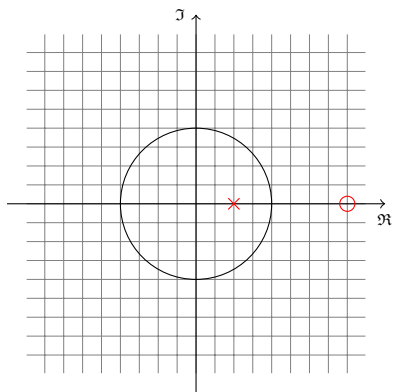


$$H(s) = \frac{a - s}{a + s}.$$

Consider the s-plane with one pole and one zero mirrored.

- ▶ These are real; they could be complex.
- ▶ There can be any number of pole zero pairs
- ▶ The frequency response is flat.

## All pass filter, z-plane



This is from applying the bilinear transform to the all-pass function.

Notice that  
if  $\alpha = 0$ ,  $H(z) = z^{-1}$ .

$$H(z) = \frac{z^{-1} - \alpha}{1 - \alpha z^{-1}}, \quad |\alpha| < 1.$$

# Mapping

Say we have an input sequence  $x_1, x_2, \dots$  and an output sequence  $y_1, y_2, \dots$ , related by

$$x_n = \sum_{k=-\infty}^{\infty} y_k \psi_{k,n}.$$

We want to find the output sequence.  
It can be shown<sup>1</sup> that to map a discrete sequence to another discrete sequence **in a way that preserves convolution**,

$$\Psi_k(z) = [\Psi_1(z)]^k.$$

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<sup>1</sup>This one I'm not going to prove

## Delay line

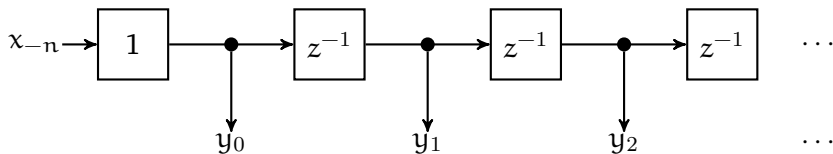
Take the trivial case, just a delay,

$$\Psi_k(z) = [z^{-1}]^k.$$

It's clear that

$$H_k(z) = z^{-k},$$

which can be expressed as a lattice like this:



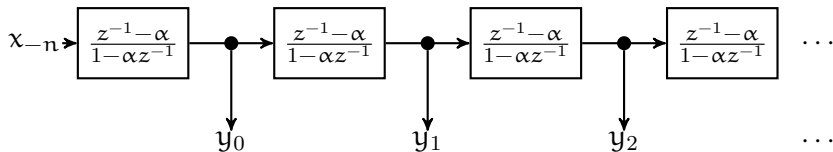


## Delay line with all-pass

What happens if

$$\Psi_k(z) = \left[ \frac{z^{-1} - \alpha}{1 - \alpha z^{-1}} \right]^k$$

You might expect something like this:

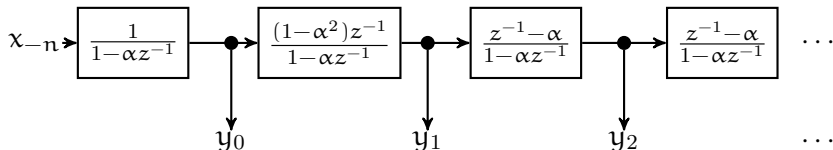


# Oppenheim's lattice

In fact, it's less clear. Oppenheim showed that

$$H_k(z) = \frac{(1 - \alpha^2)z^{-1}}{(1 - \alpha z^{-1})^2} \left[ \frac{z^{-1} - \alpha}{1 - \alpha z^{-1}} \right]^{k-1}, \quad H_0(z) = \frac{1}{1 - \alpha z^{-1}}.$$

which is

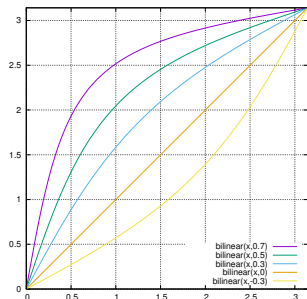


i.e., there is a small edge effect.

## So what?

- ▶ The all-pass maps magnitude to magnitude.  
⇒ The unit circle is mapped to the unit circle.
- ▶ The all pass messes with the **phase**.  
⇒ The lattice of Oppenheim implements a **frequency warp**.

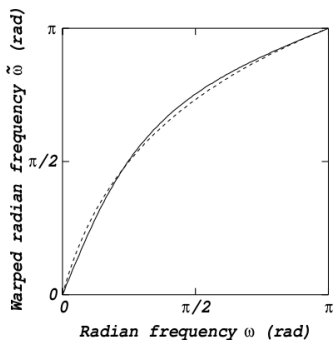
# Frequency warp



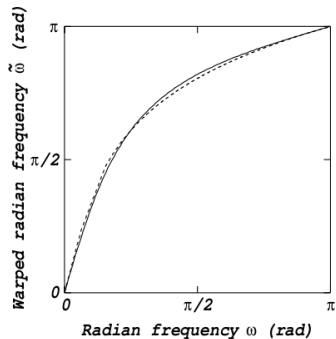
The frequency warp function is the phase response of the all-pass.

$$\tilde{\omega} = \omega + 2 \tan^{-1} \left( \frac{\alpha \sin \omega}{1 - \alpha \cos \omega} \right).$$

# Uses for bilinear transform



(a) mel scale ( $\alpha = 0.42$ )



(b) Bark scale ( $\alpha = 0.55$ )

Most common is as an approximation to Bark or mel.

## Warpable things

It's possible to warp anything that has a network with  $z^{-n}$ :

- ▶ Obviously, time domain samples.
- ▶ Cepstra.
- ▶ Autoregression coefficients.
- ▶ Linear prediction coefficients.

Beware: A **finite sequence** is warped to an **infinite sequence**.

- ▶ The (truncated) warped sequence is not a complete representation.
- ▶ It's not necessarily invertible.  
But it is if you use (say) enough cepstra

# Inversion

However, the most useful aspect of the bilinear transform is that it is invertible.

- ▶ No binning.
- ▶ Can be used for recognition **and** synthesis.

## It's a linear transform

The lattice amounts to multiplication by this matrix:

$$\begin{pmatrix} 1 & \alpha & \alpha^2 & \dots & \alpha^{M-1} \\ 0 & 1 - \alpha^2 & 2\alpha(1 - \alpha^2) & \dots & (M-1)\alpha^{M-2}(1 - \alpha^2) \\ 0 & -\alpha(1 - \alpha^2) & \dots & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & -1^M \alpha^{M-2}(1 - \alpha^2) & \dots & \dots & \dots \end{pmatrix}$$

i.e., A frequency warp is a linear transform of the cepstrum!



Vocal Tract Length Normalisation.

- ▶ Alter the warping a bit depending on VTL.
- ▶ Effectively warp more for males, less for females.

but more later...

# Root cepstrum

# Spectral compression

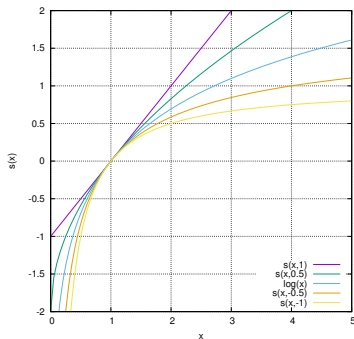
Oppenheim's homomorphic approach suggests using the (complex) logarithm.

- ▶ Useful to linearise convolutional effects.
- ▶ Fairly “nice” framework.
- ▶ Sensitive to small spectral values.

Hermansky's PLP uses the cube root of power spectrum.

- ▶ Somewhat closer to the form of human hearing.
- ▶ Naturally floored at zero.
- ▶ Is cube root really the right root?

# Generalised logarithm



Say we define a function

$$s_\gamma(x) = \frac{x^\gamma - 1}{\gamma}.$$

How does it behave?

## Inverse

The inverse function is

$$s_\gamma^{-1} = (1 + \gamma x)^{1/\gamma}.$$

Apply this to the z-transform representation of the cepstrum

$$\hat{H}(z) = \sum_{m=-\infty}^{\infty} c_m z^{-m} \approx \sum_{m=0}^M c_m z^{-m}.$$

Gives

$$H(z) = \begin{cases} \left( 1 + \gamma \sum_{m=0}^M c_m z^{-m} \right)^{\frac{1}{\gamma}}, & 0 < |\gamma| \leq 1, \\ \exp \sum_{m=0}^M c_m z^{-m}, & \gamma = 0. \end{cases}$$

# A generalised analysis

Different values of  $\gamma$  correspond to different traditional analyses:

- $\gamma = 0$  Cepstrum. The generalised log reverts to the usual log.
- $\gamma = -1$  All pole. But note that no optimisation criterion is specified yet.
- $\gamma = 1$  All zero. In practice not that useful.

The most useful is  $\gamma = -1$ :

- ▶ The generalised logarithm has the same z-transform as an all pole model
- ▶ It's not a maximum likelihood fit though!

# Optimality & UELS

So far it's defined backwards

- ▶ If we calculate a root-cepstrum, it can be thought of as an LP model.
- ▶ It's not optimal in any LP sense!

To make it optimal, you have to define an optimisation criterion.

Unbiased Estimation of Log Spectrum<sup>2</sup>

- ▶ An iterative algorithm to estimate parameters  $c_m$ .
- ▶ If  $\gamma = -1$ , amounts to the same LMS criterion as LPC.

For  $0 < |\gamma| \leq 1$ , UELS will give **an** optimal representation in terms of  $c_m$ .

- ▶ You still need to convert the result to the cepstrum if  $\gamma \neq 1$ .

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<sup>2</sup>Which I ain't going to explain.

# Uses

Root cepstrum is not quite the same as the homomorphic logarithm

- ▶ Doesn't quite linearise convolutional noise.
- ▶ The result is not quite a cepstrum.

However,

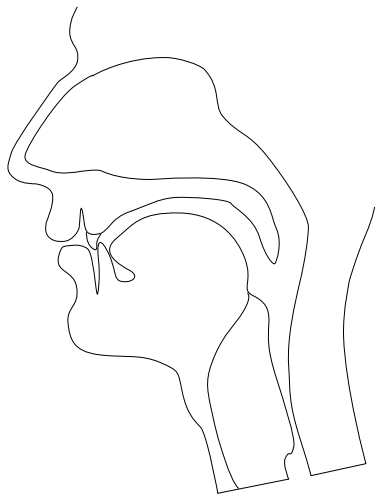
- ▶ It does tend to give good results sometimes.
- ▶ Especially in noise.

Root cepstrum is most useful as a theoretical tool to unify several different approaches.



# Vocal Tract Length Normalisation

# VTLN



VTLN is inspired by the vocal tract.

- ▶ Vocal tract length is different for different people.
- ▶ Men have longer tracts than women.

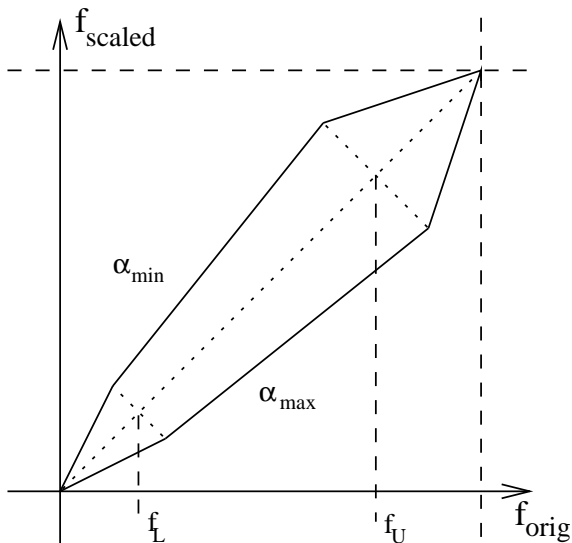
# Principle

The general idea is to warp spectra to compensate for vocal tract length. Two ways to do it:

1. Build the warping into the warping that is done for perceptual reasons.
2. Add another warp on top of that warping.

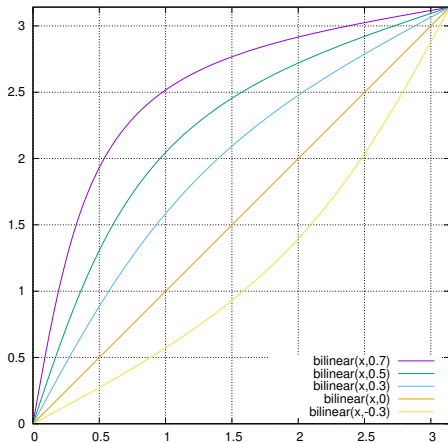
In practice, these blur into one...

# The HTK kite



(From the HTK book)

# The bilinear warp



# Pros and cons

## Kite

- ▶ Easy to implement.
- ▶ Too many parameters.
- ▶ Not clear what the final transformation is.

## Bilinear

- ▶ Easy to implement, but a little slow.
- ▶ only one parameter.
- ▶ Can be applied to cepstra

...and in fact the bilinear transform is a linear transform in cepstral space.

## Concatenating two bilinear warps

- ▶ Say we have a value,  $\alpha_1 \approx 0.42$ , for the perceptual warping.
- ▶ Concatenate a second warp,  $\alpha_2 \approx 0.05$ , for the VTLN.
- ▶ The total warp is actually a single warp with

$$\alpha = \frac{\alpha_1 + \alpha_2}{1 + \alpha_1 \alpha_2}.$$

# How to calculate the warp factor?

In a theoretically uninspiring way!

- ▶ Calculate cepstra for several values of the warp factor.
- ▶ Use the one that “works best”

“Works best” can be

- ▶ Highest likelihood given a (speech recognition) model.
- ▶ Good speech recognition performance.
- ▶ Sounds nicest.



## Is it worth it?

VTLN can respond to small amounts of training data

- ▶ It's useful for both recognition and synthesis
- ▶ This is what Lakshmi's thesis was about

However, remember that VTLN is a linear transform in the cepstrum!

- ▶ It will be subsumed by adaptation linear transforms.
- ▶ For moderate amounts of training data, feature space MLLR is better