# Spectral Audio Modeling: Why Did It Evolve and Do We Need It Now?

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ADC-23

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# Overview

## Goal:

A *zoomed-out overview* of spectral audio modeling, from evolution to AI

## Intended Audience:

- Audio signal-processing engineers interested in latest AI audio developments
- AI practitioners interested in more about audio signal-processing techniques

## Relevant Questions:

- Why did we evolve spectrum analyzers in our ears?
- How did that drive our use of spectrum analysis and processing?
- How did AI pick up on all that, and will explicit spectra even survive in AI?



# Outline of Topics

- Human Hearing
- Why Spectra?
- Spectral Synthesis
- AI Audio Synthesis
- Spectra in AI

## Download These Overheads

- Downloadable from the ADC23 website
- or the JOS Home Page at CCRMA
  (Web-search for "Julius Smith CCRMA"):
  `https://ccrma.stanford.edu/~jos/pdf/ADC23.pdf`
- *Click on the many sound-example links!*



# CCRMA Spectral Modeling Origins

Stanford AI Lab (SAIL) 60s-80s


John Chowning

Stanford Knoll (main campus)

Max Mathews

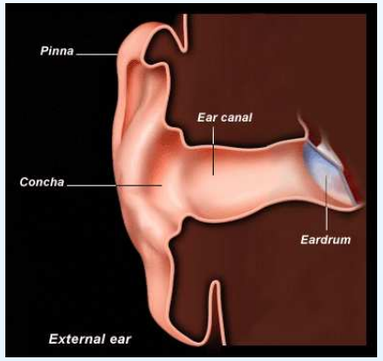
CCRMA was at SAIL (60s-80s) then The Knoll (President's Residence then Music Dept.)



# JOS Courses Developed

- **Music 320A**: AUDIO SPECTRUM ANALYSIS
- **Music 320B**: AUDIO FILTER ANALYSIS AND STRUCTURES
- **Music 420A**: **PHYSICAL** AUDIO SIGNAL PROCESSING
- **Music 421A**: **TIME-FREQUENCY** AUDIO SIGNAL PROCESSING

420A

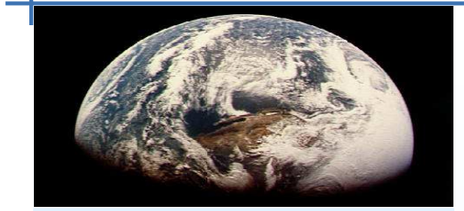



421A

All four textbooks **free online**

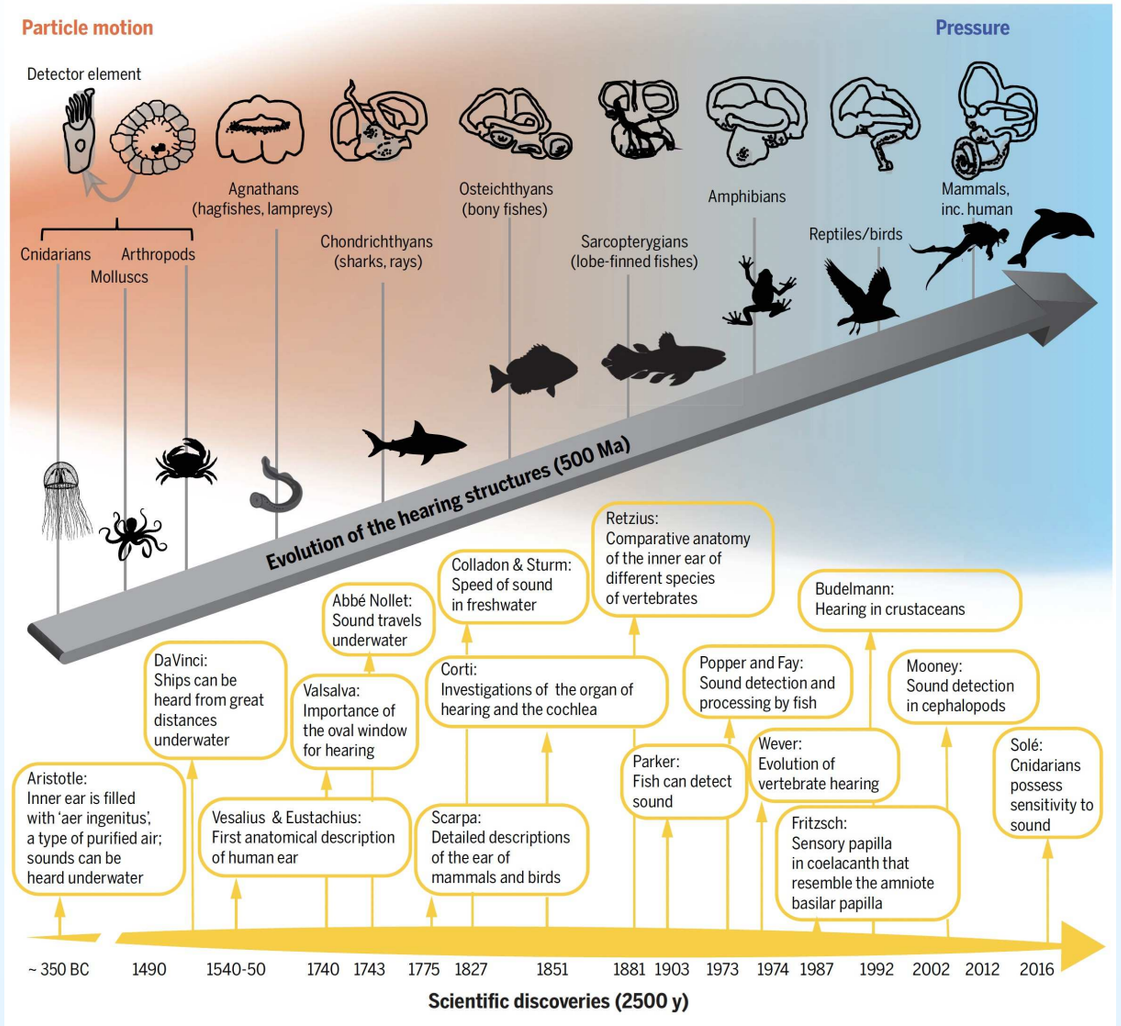


# Early Spectral Audio Processing





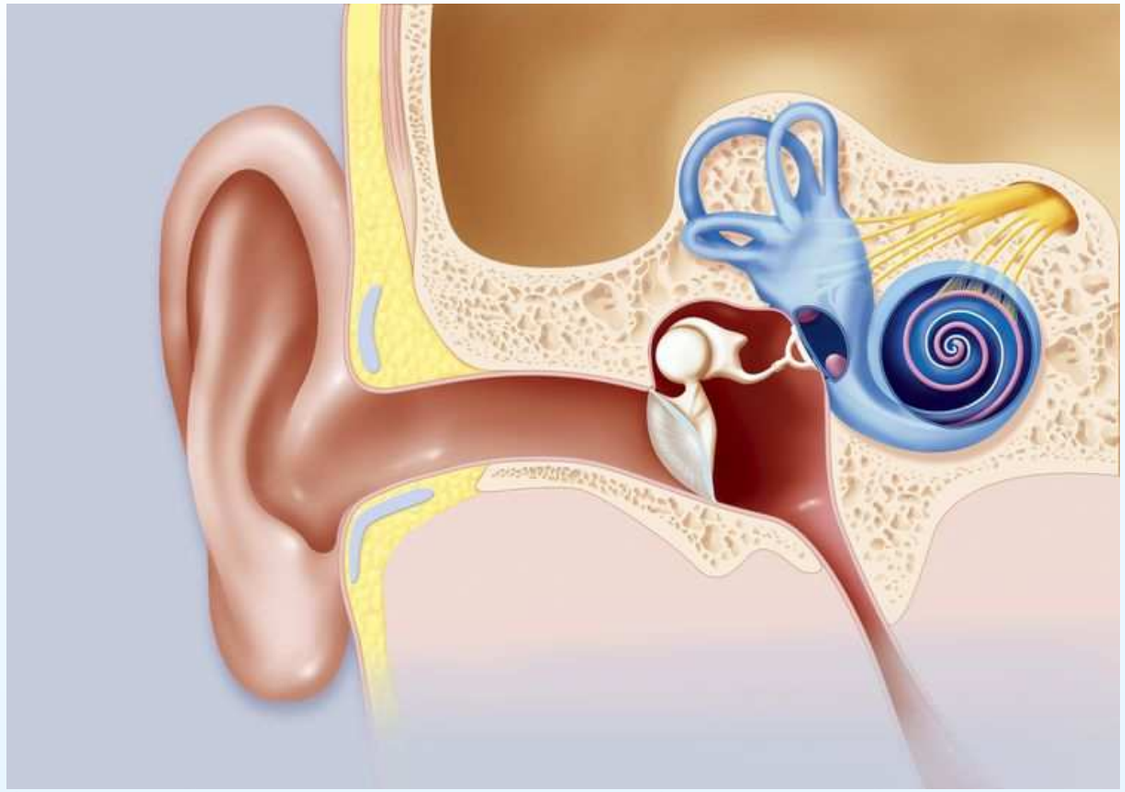
# Evolution of Hearing




http://science.sciencemag.org/



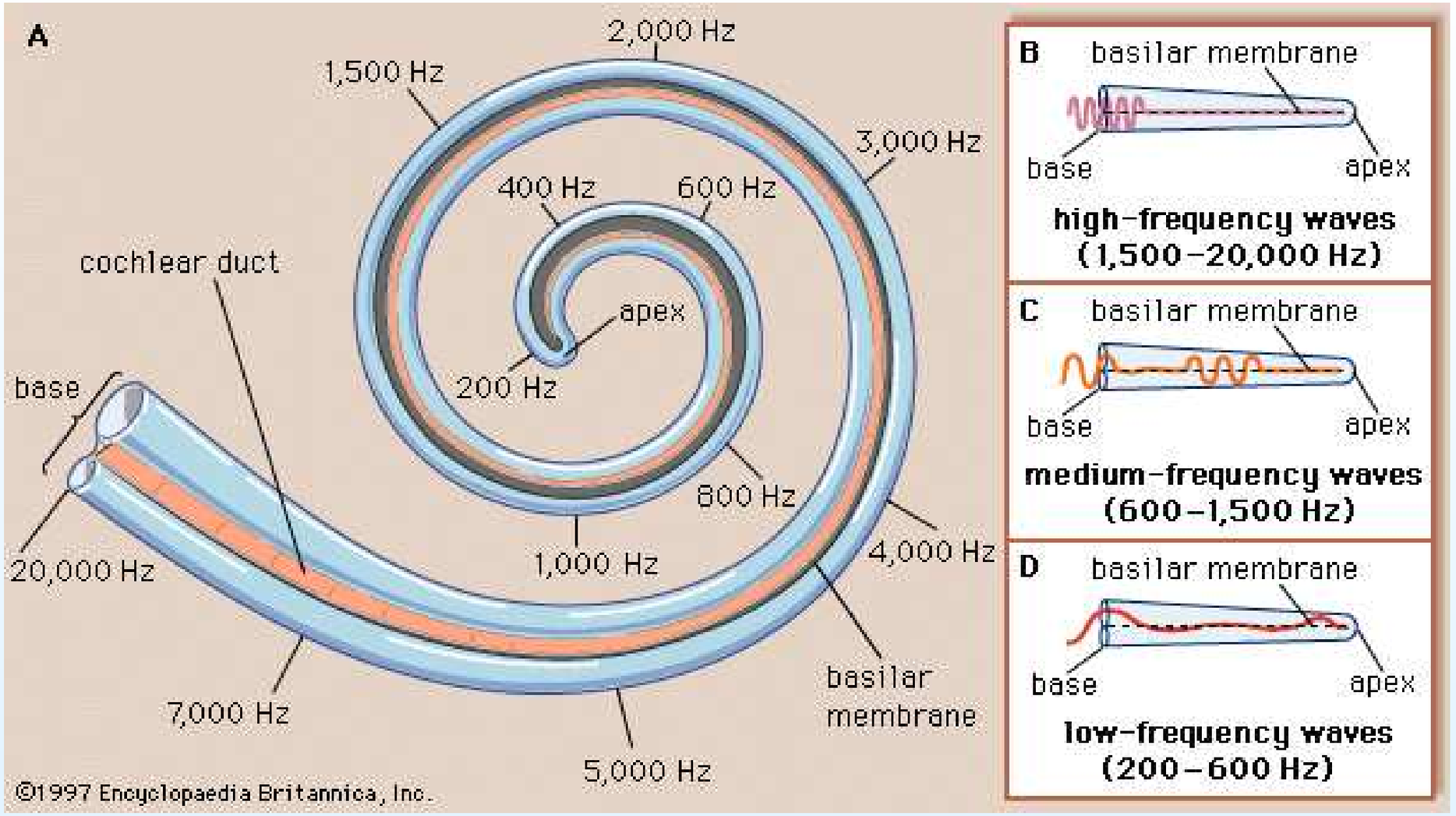
# Human Ears



https://www.verywellhealth.com/cochlea-anatomy-5069393



# Inner Ear Spectral Processor




https://www.britannica.com



# First Known Polyphonic Spectral Audio Synthesis

https://www.classicfm.com

- Greek “Hydraulis” Organ
- aka “Water Organ”
- 3rd Century BC
- This one from ≈1435 AD
- Direct manipulation of pitch
- Neanderthal bone flutes are said to go back 60k years,
  so they win in the “mono” category
- Aurignacian flutes (bone and ivory) said to be created 43k-35k years ago

Pipe organs did complex “additive synthesis” (before “sinusoids”)



# Telharmonium (1898)

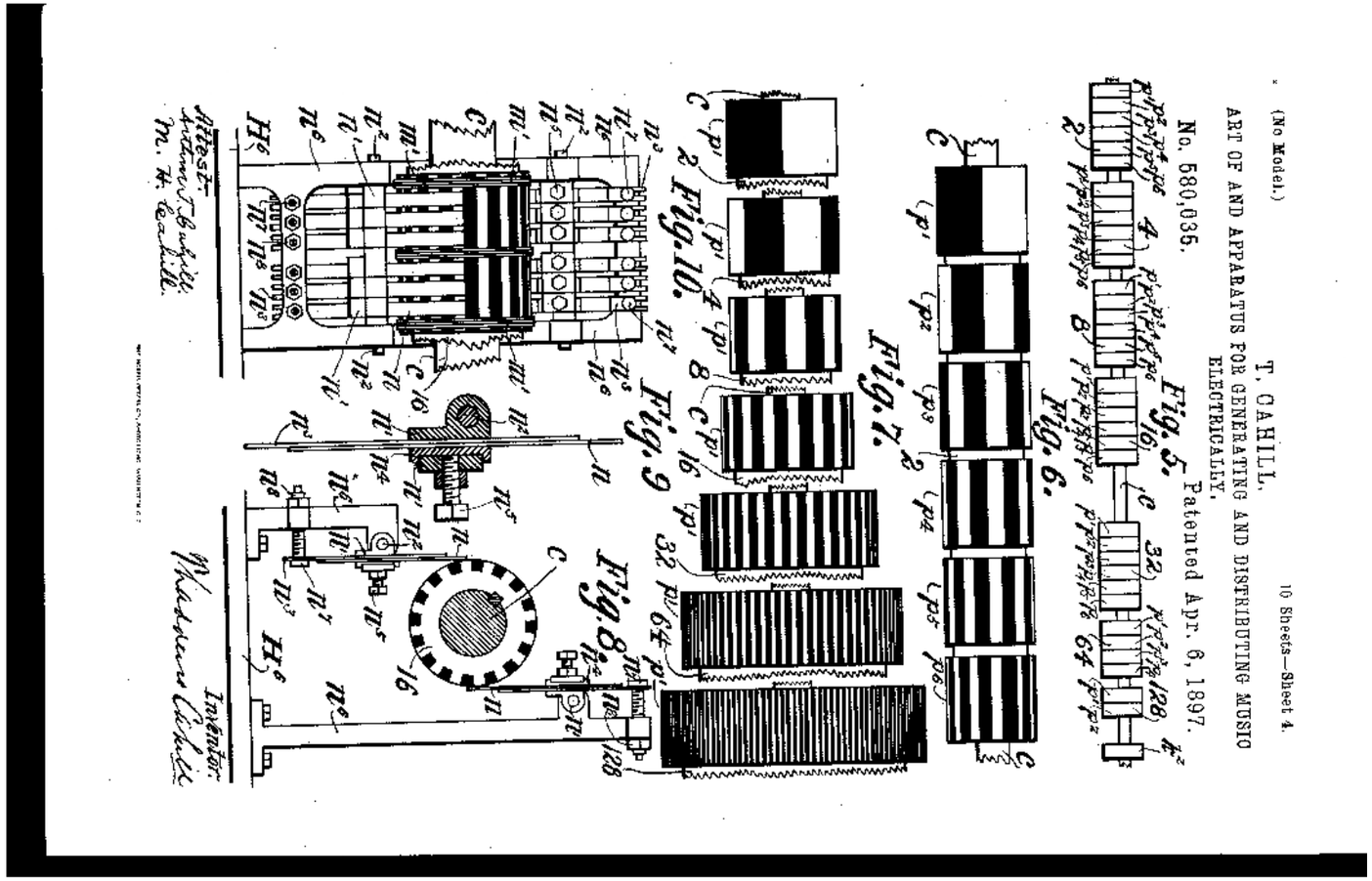
## Telharmonium (Cahill 1898)

U.S. patent 580,035:

"Art of and Apparatus for Generating and Distributing Music Electrically"

# Telharmonium Rheotomes

## Forerunner of the Hammond Organ Tone Wheels



(No Model.) 10 Sheets—Sheet 4.

T. CAHILL,

ART OF AND APPARATUS FOR GENERATING AND DISTRIBUTING MUSIC ELECTRICALLY.

No. 580,035. Patented Apr. 6, 1897.

Fig. 5.

Fig. 6.

Fig. 7.

Fig. 10.

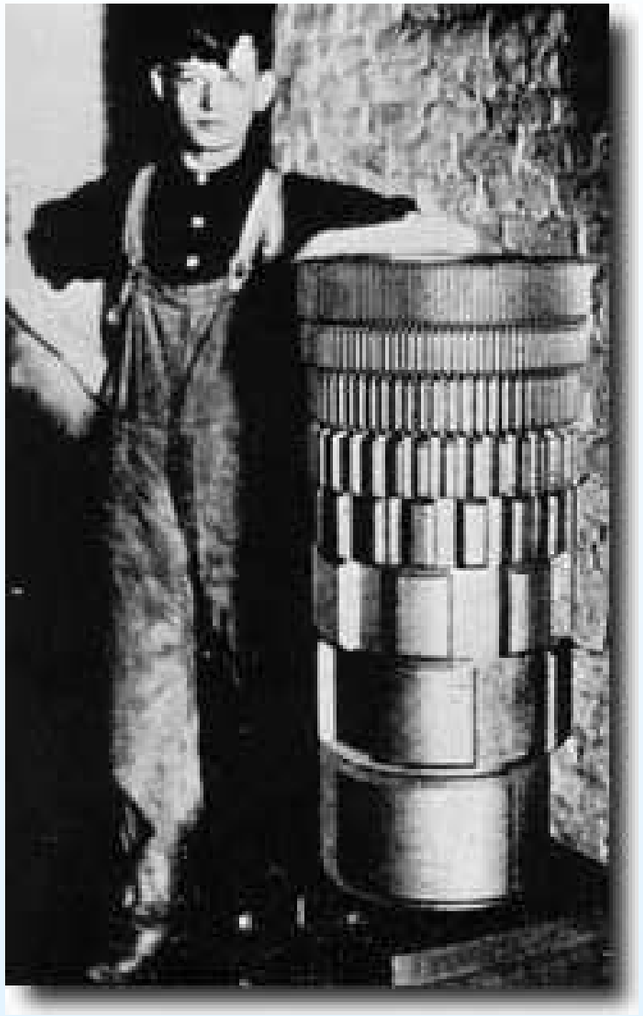
Fig. 9

Fig. 8.

Witnesses: Arthur F. Burdett, M. W. Baldwin.

Inventor: Thaddeus Cahill

## Telharmonium Rotor (early “Tonewheel”)



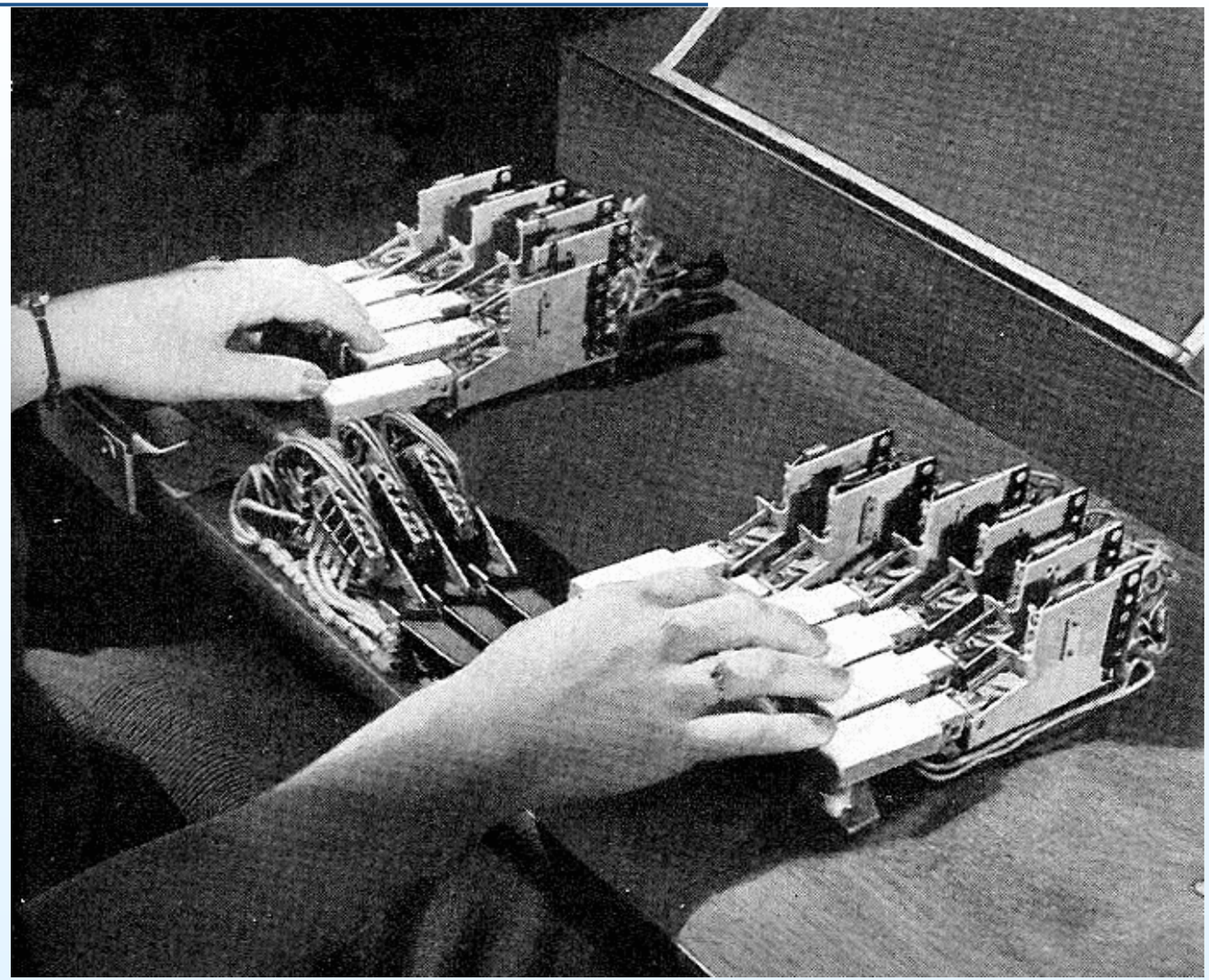
Hammond influenced: `https://en.wikipedia.org/wiki/Tonewheel`



# The Voder (1939)



# The Voder (Homer Dudley — 1939 Worlds Fair)



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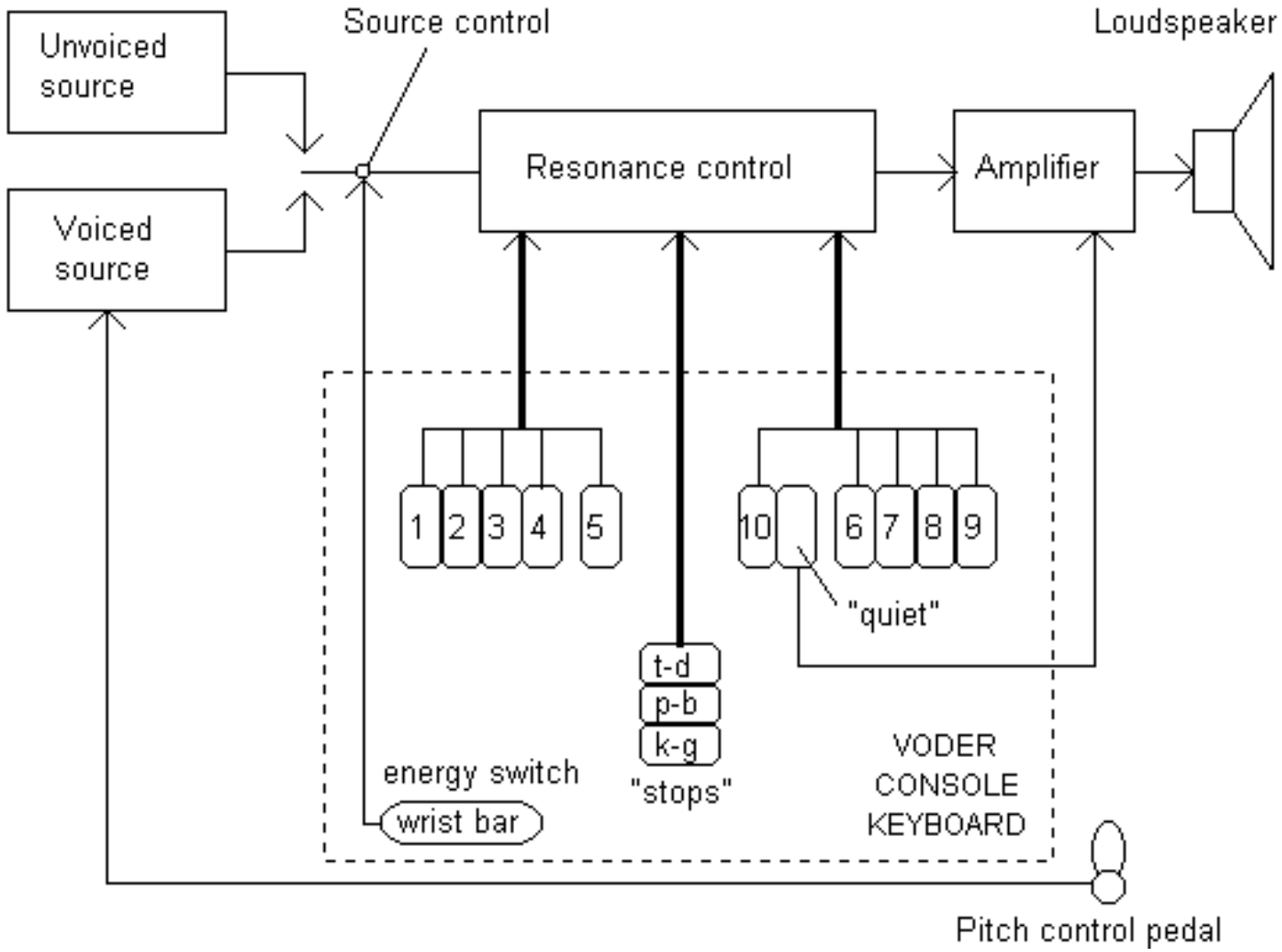
http://davidszondy.com/future/robot/voder.htm



# Voder Keyboard




http://www.acoustics.hut.fi/publications/files/theses/lemmetty_mst/chap2.html — (from Klatt 1987)



# Voder Schematic

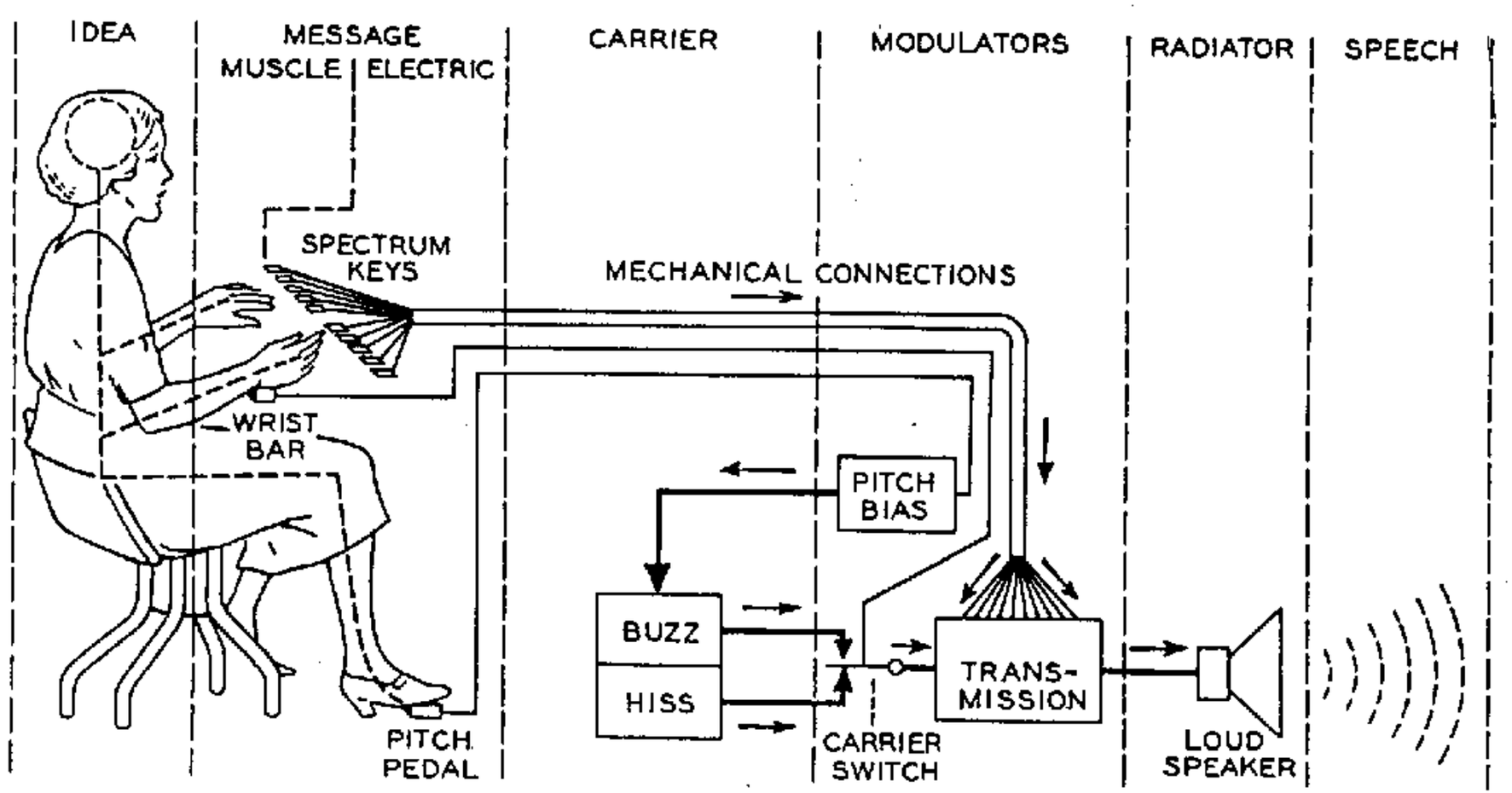



Fig. 8—Schematic circuit of the voder.

http://ptolemy.eecs.berkeley.edu/~eal/audio/voder.html



# Voder Demos

- Voder Demo (Audio and Video)
- More Voder Demos - Audio Only [Demos Begin]



# Channel Vocoder (1928)
# (“Voice Coder”)



# Vocoder Analysis & Resynthesis (Dudley 1928)

## Analysis:

- Ten analog bandpass filters between 250 and 3000 Hz: Bandpass $\rightarrow$ rectifier $\rightarrow$ lowpass filter $\rightarrow$ *amplitude envelope*
- Voiced/Unvoiced decision made
- Fundamental frequency $F_0$ measured for voiced case

## Synthesis:

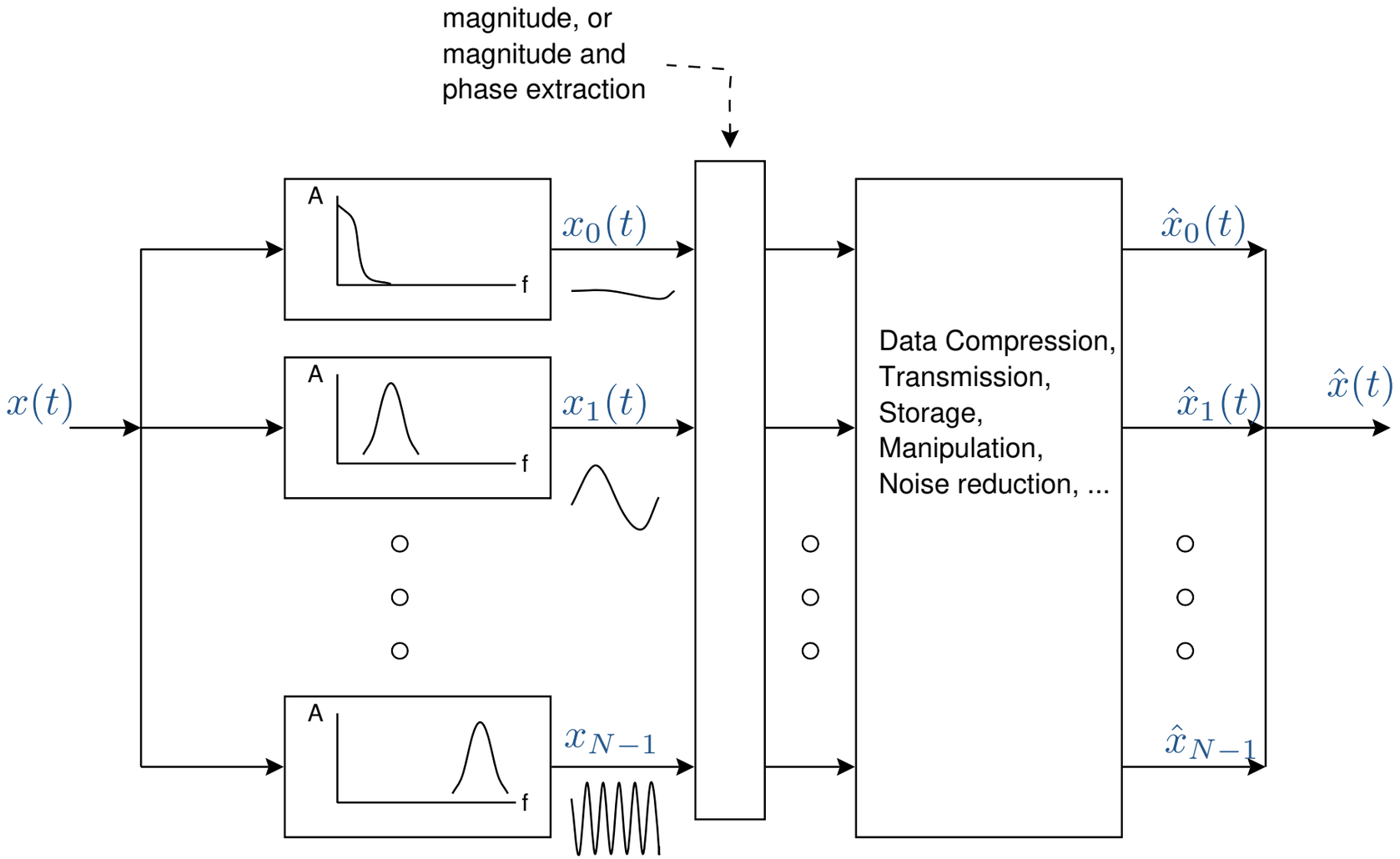
- Ten matching bandpass filters driven by a
  - “buzz source” (voiced), or
  - “hiss source” (unvoiced)
- Bands were scaled by amplitude envelopes and summed
- Said to have an “unpleasant electrical accent”

## Related Speech Models:

- The Vocoder is an early *source-filter* model for speech
- *Linear Predictive Coding* (LPC) of speech is another



# Vocoder Filter Bank Analysis/Resynthesis





# Channel Vocoder Sound Examples

- Original

- 10 channels, sine carriers
- 10 channels, narrowband-noise carriers

- 26 channels, sine carriers
- 26 channels, narrowband-noise carriers
- 26 channels, narrowband-noise carriers, channels reversed

- ***Phase* Vocoder:** Identity system in absence of modifications

- The FFT Phase Vocoder next transitioned to the Short-Time Fourier Transform (STFT) (Allen and Rabiner 1977)

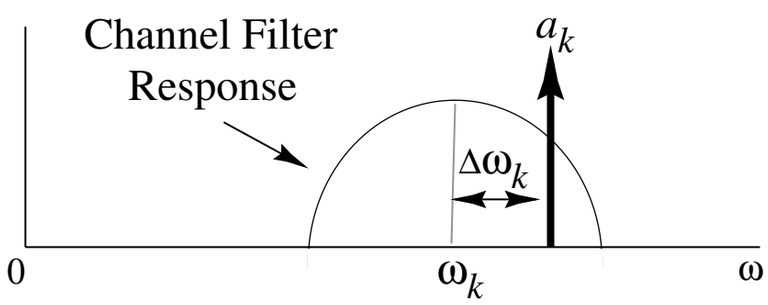


# The Phase Vocoder (1966)

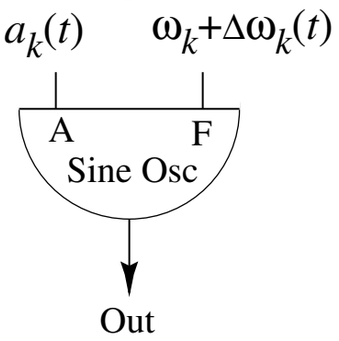


# Phase Vocoder Analysis for Additive Synthesis (1976)

**Analysis Model**



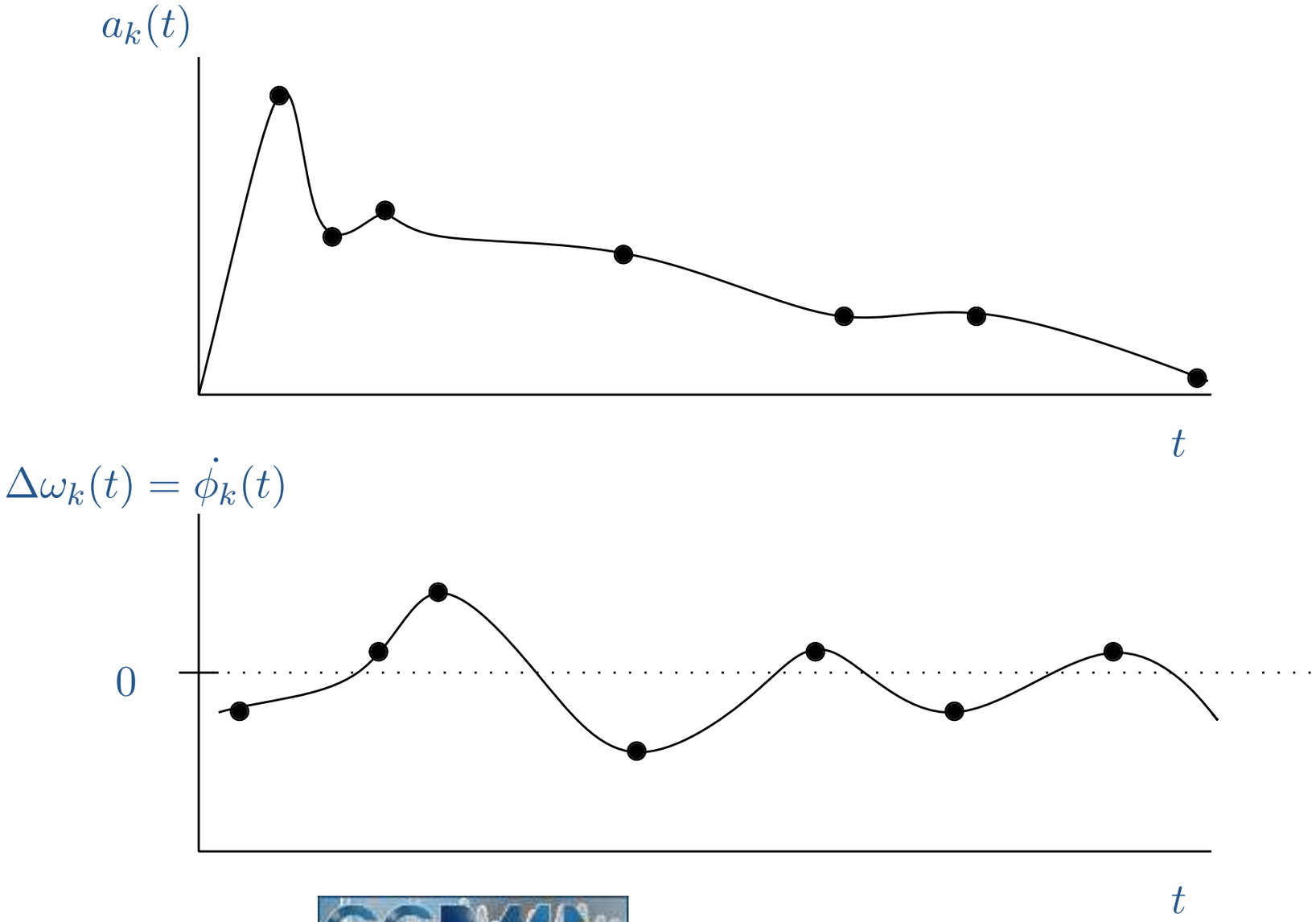

**Synthesis Model**




- Early “channel vocoder” implementations (hardware) only measured amplitude $a_k(t)$ (Dudley 1939)
- The “phase vocoder” (Flanagan and Golden 1966)
  added phase tracking in each channel
- Portnoff (1976) developed the FFT phase vocoder, replacing the heterodyne comb in computer-music additive-synthesis analysis (James A. Moorer 1975)
- Inverse FFT synthesis (Rodet and Depalle 1992) gave faster sinusoidal oscillator banks



# Amplitude and Frequency Envelopes

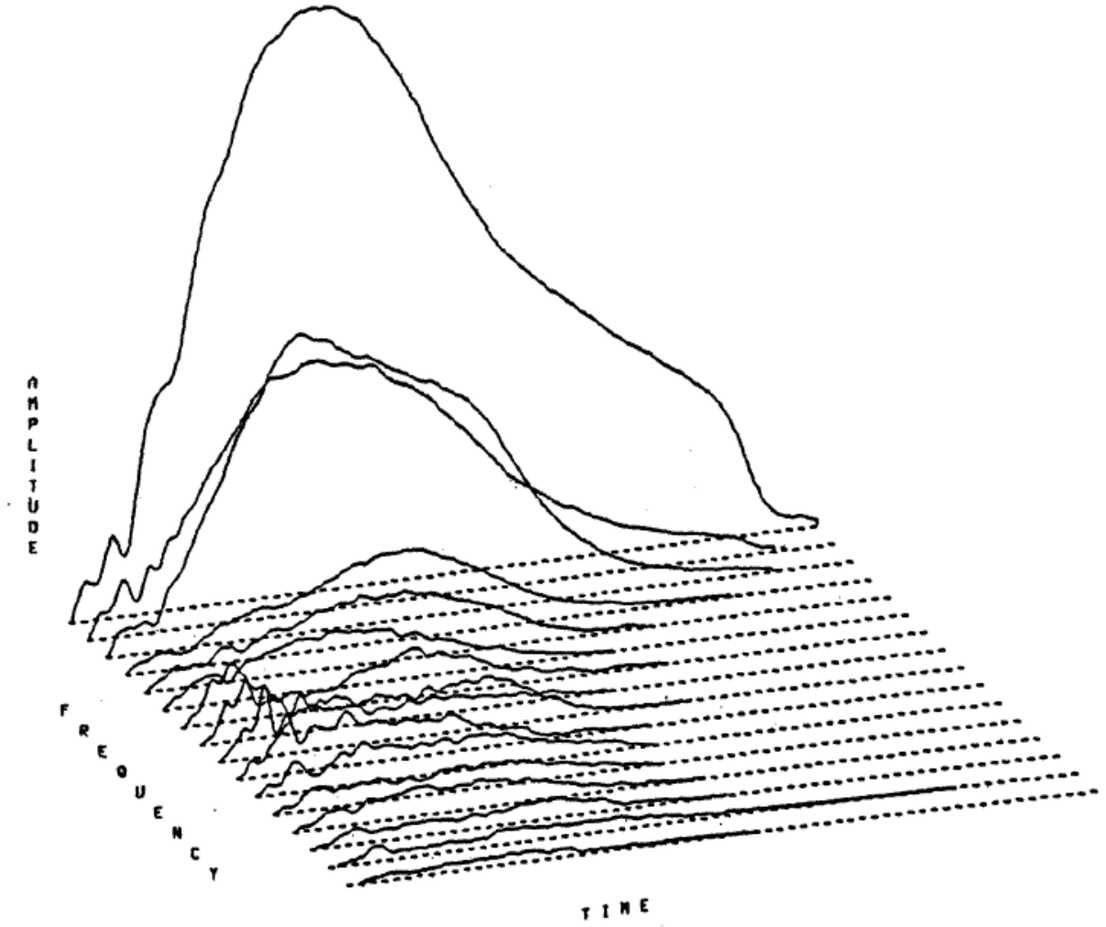




# Additive Synthesis (1969)



# Classic Additive-Synthesis Analysis (Heterodyne Comb)

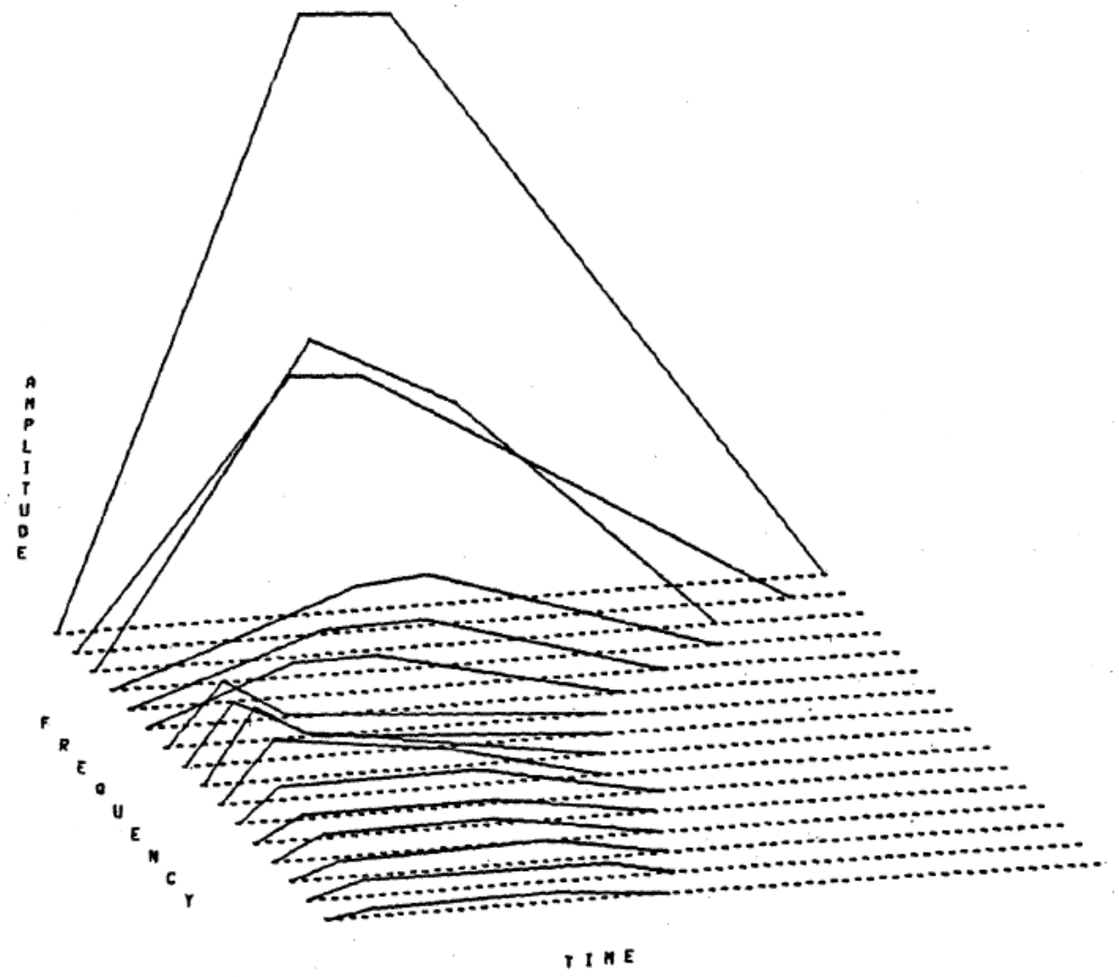



John Grey 1975 — CCRMA Tech. Reports 1 & 2

(CCRMA “STANM” reports — available online)



# Classic Additive-Synthesis (Sinusoidal Oscillator Envelopes)

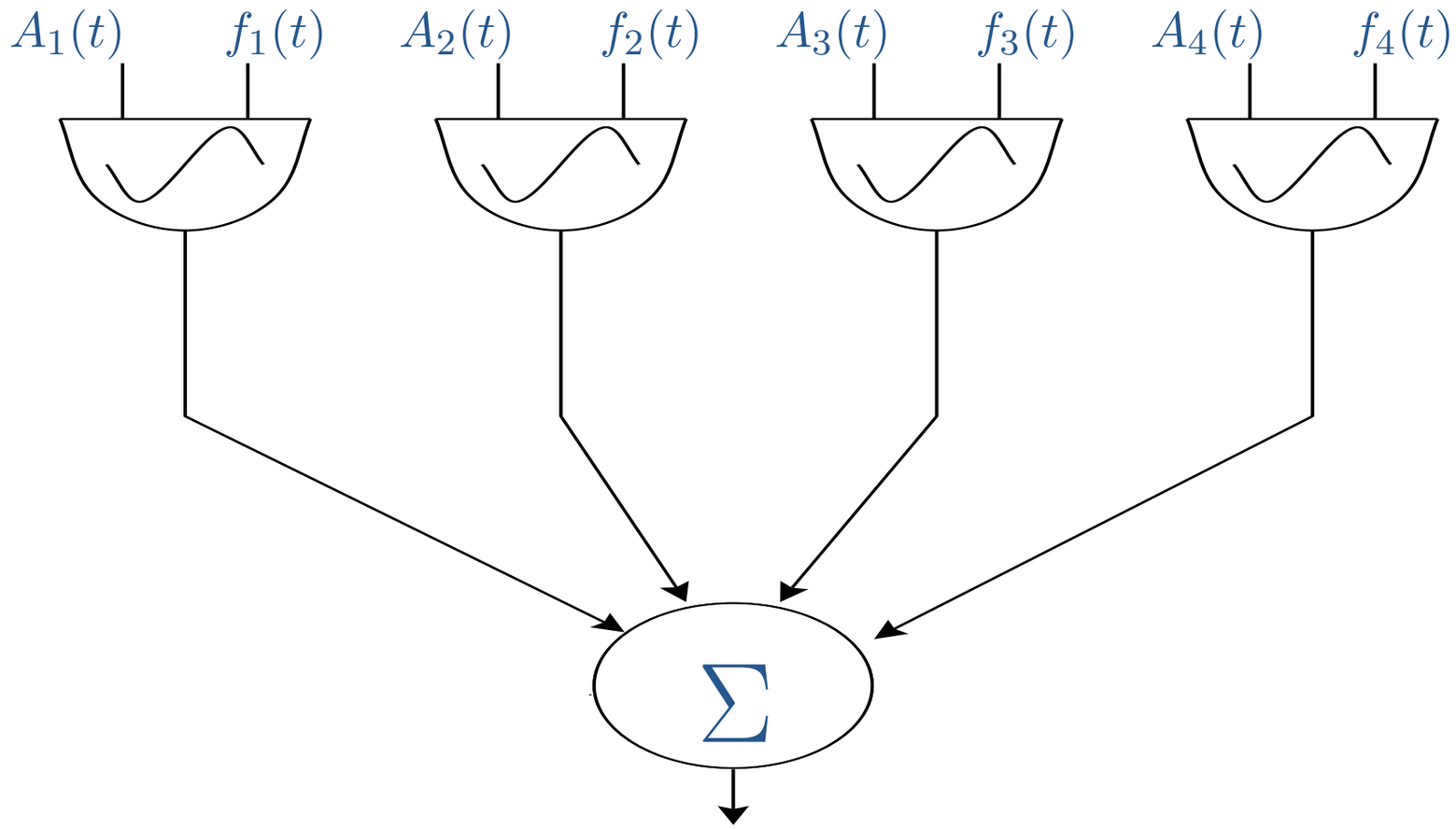



John Grey 1975 — CCRMA Tech. Reports 1 & 2

(CCRMA “STANM” reports — available online)



# Classic Additive Synthesis Diagram (Computer Music, 1960s)




$$y(t) = \sum_{i=1}^{4} A_i(t) \sin\left[\int_0^t \omega_i(t)dt + \phi_i(0)\right]$$

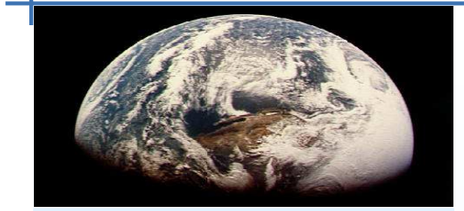


# Classic Additive-Synthesis Examples

- Bb Clarinet
- Eb Clarinet
- Oboe
- Bassoon
- Tenor Saxophone
- Trumpet
- English Horn
- French Horn
- Flute

- All of the above
- Independently synthesized set

(Synthesized from original John Grey data)





# Frequency Modulation Synthesis (1973)



# Frequency Modulation (FM) Synthesis

FM synthesis is normally used as a *spectral modeling* technique

- Discovered and developed (1970s) by John M. Chowning (CCRMA Founding Director)
- Key paper: JAES 1973 (vol. 21, no. 7)
- Commercialized by Yamaha Corporation:
  - DX-7 synthesizer (1983)
  - OPL chipset (SoundBlaster PC sound card)
  - Cell phone ring tones

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- On the physical modeling front, synthesis of vibrating-string waveforms using *finite differences* started around this time:
  Hiller & Ruiz, JAES 1971 (vol. 19, no. 6)



# FM Formula

$$x(t) = A_c \sin[\omega_c t + \phi_c + A_m \sin(\omega_m t + \phi_m)]$$

where

$(A_c, \omega_c, \phi_c)$ specify the *carrier* sinusoid
$(A_m, \omega_m, \phi_m)$ specify the *modulator* sinusoid

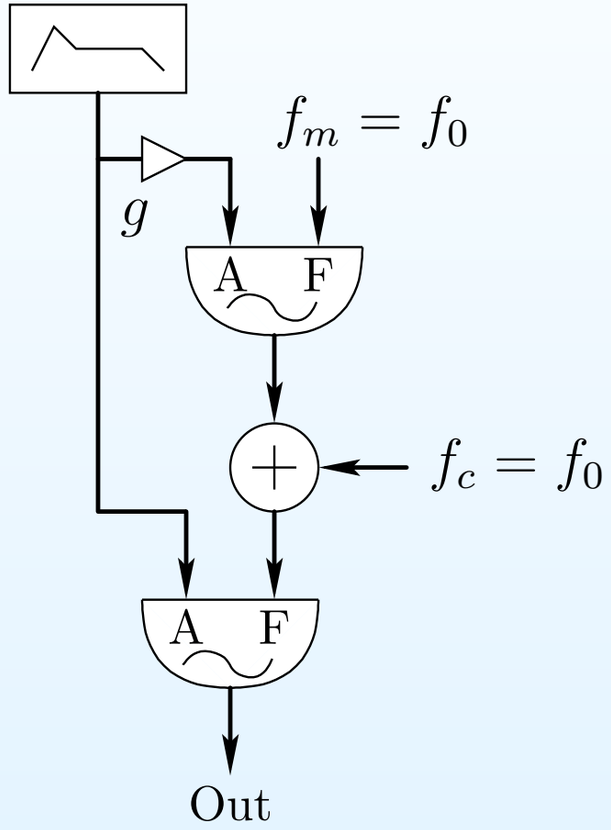
Can also be called *phase modulation*



# Simple FM "Brass" Patch (Chowning 1970–)

Jean-Claude Risset observation (1964–1969):

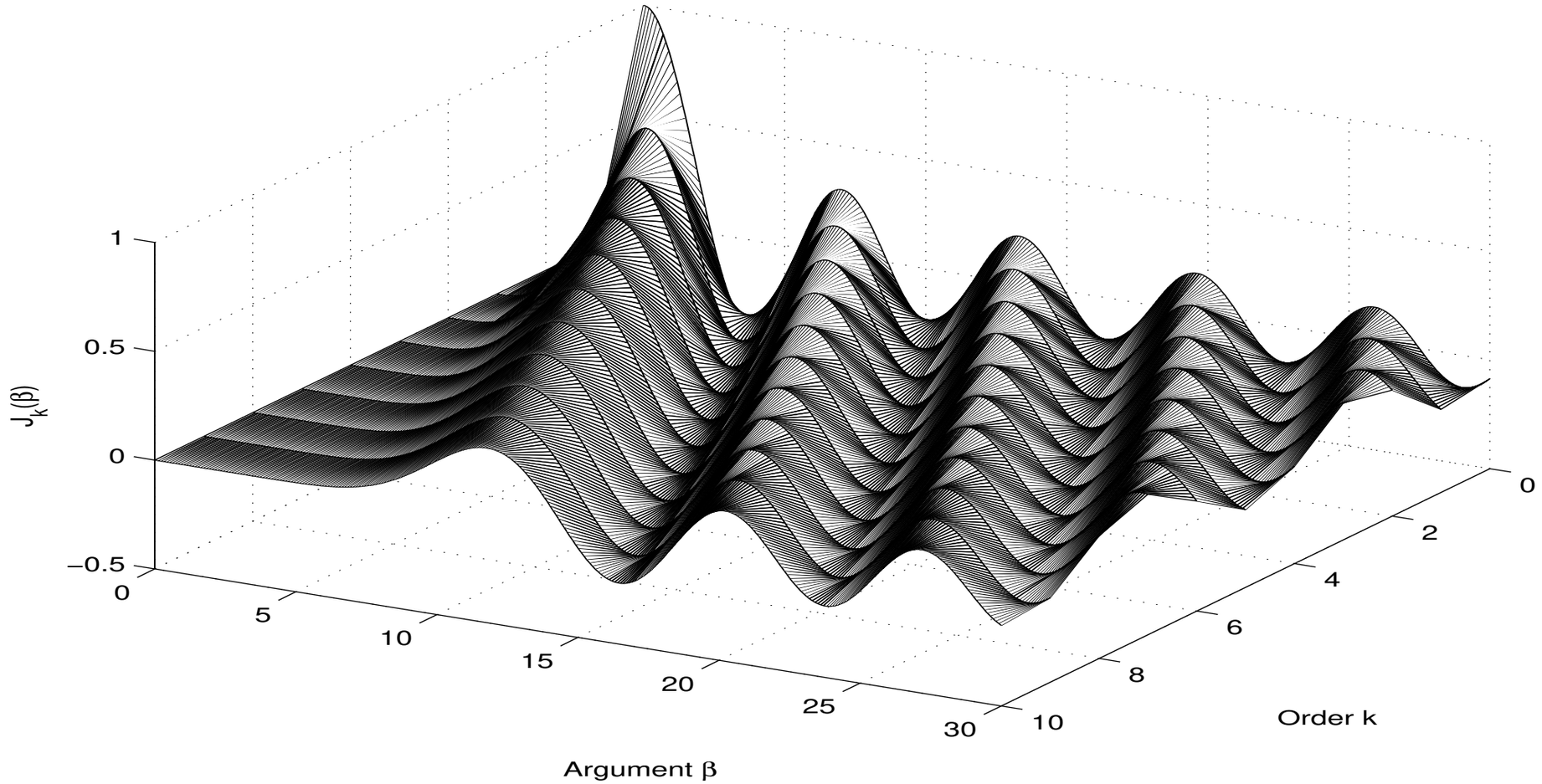
Brass bandwidth $\propto$ amplitude





# FM Harmonic Amplitudes (Bessel Function of First Kind)

Harmonic number $k$, FM index $\beta$:





## Frequency Modulation (FM) Examples

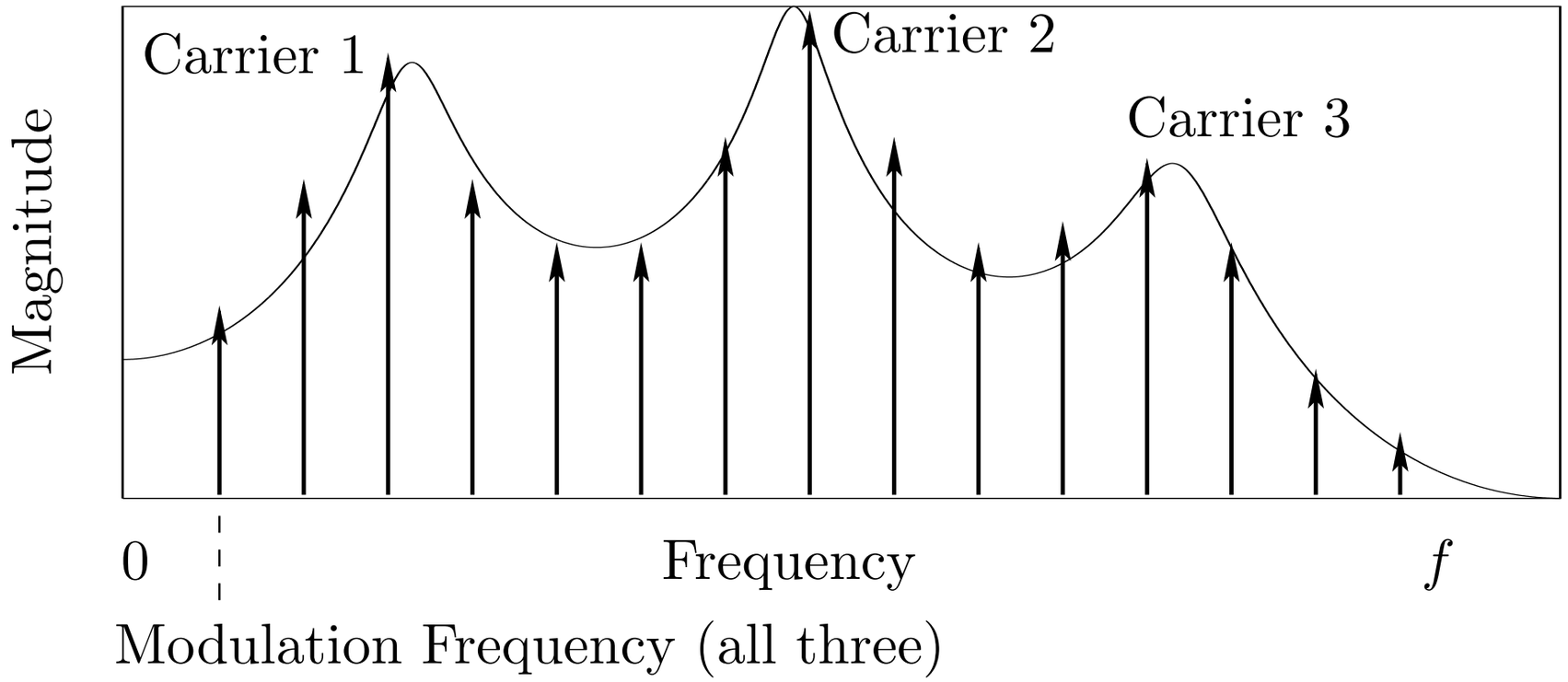
All examples by John Chowning unless otherwise noted:

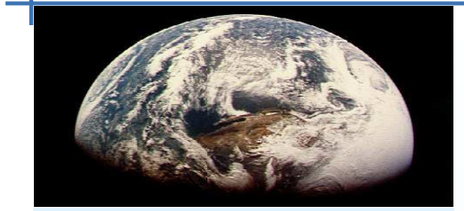
- FM brass synthesis
  - Low Brass example
  - Dexter Morril's FM Trumpet
- FM singing voice (1978)
  Each formant synthesized using an FM operator pair
  (two sinusoidal oscillators)
  - Chorus
  - Voices
  - Basso Profundo
- Other early FM synthesis
  - Clicks and Drums
  - Big Bell
  - String Canon

# FM Voice



FM voice synthesis can be viewed as *compressed modeling of spectral formants*



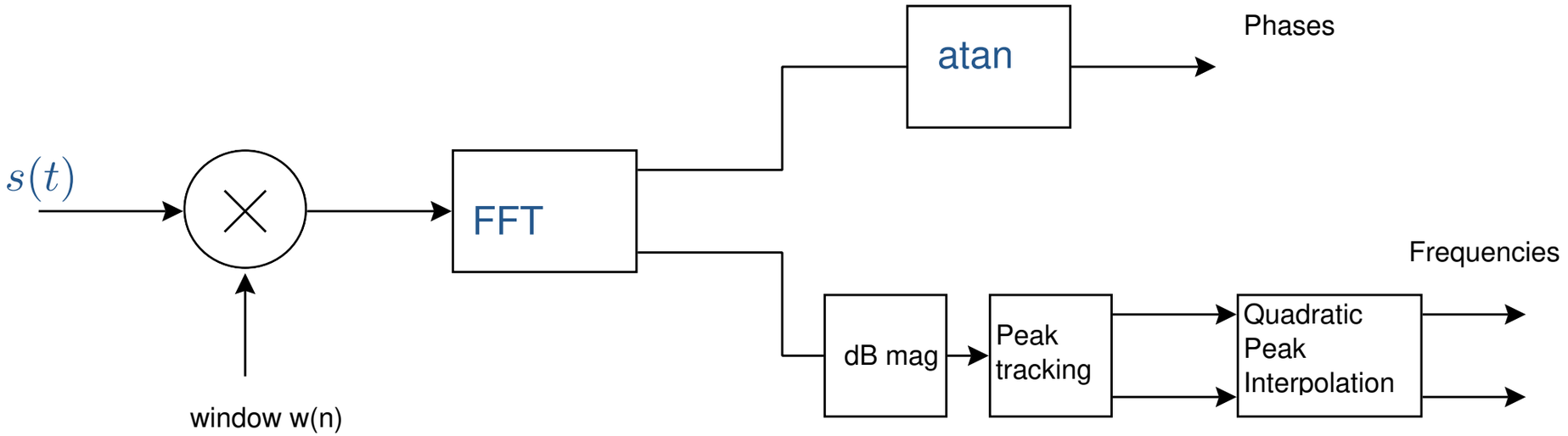




# Sinusoidal Modeling Synthesis (1988)



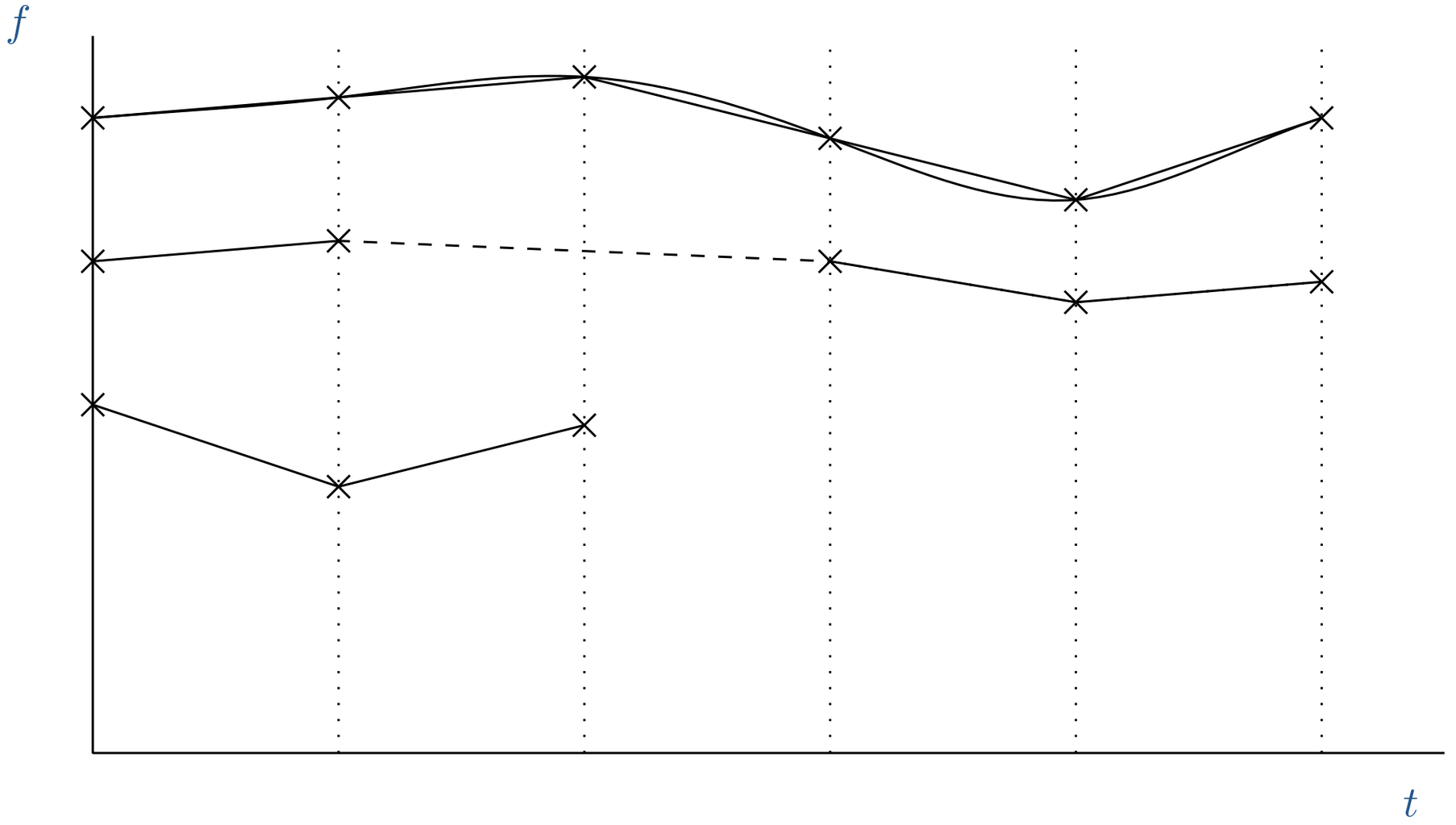
# Tracking Spectral Peaks in the Short-Time Fourier Transform




- STFT peak tracking at CCRMA: mid-1980s (PARSHL program)
- Motivated by vocoder analysis of piano tones
- Influences: STFT (Allen and Rabiner 1977), ADEC (1977), MAPLE (1979)
- Independently developed for speech coding by McAulay and Quatieri at Lincoln Labs (1985)

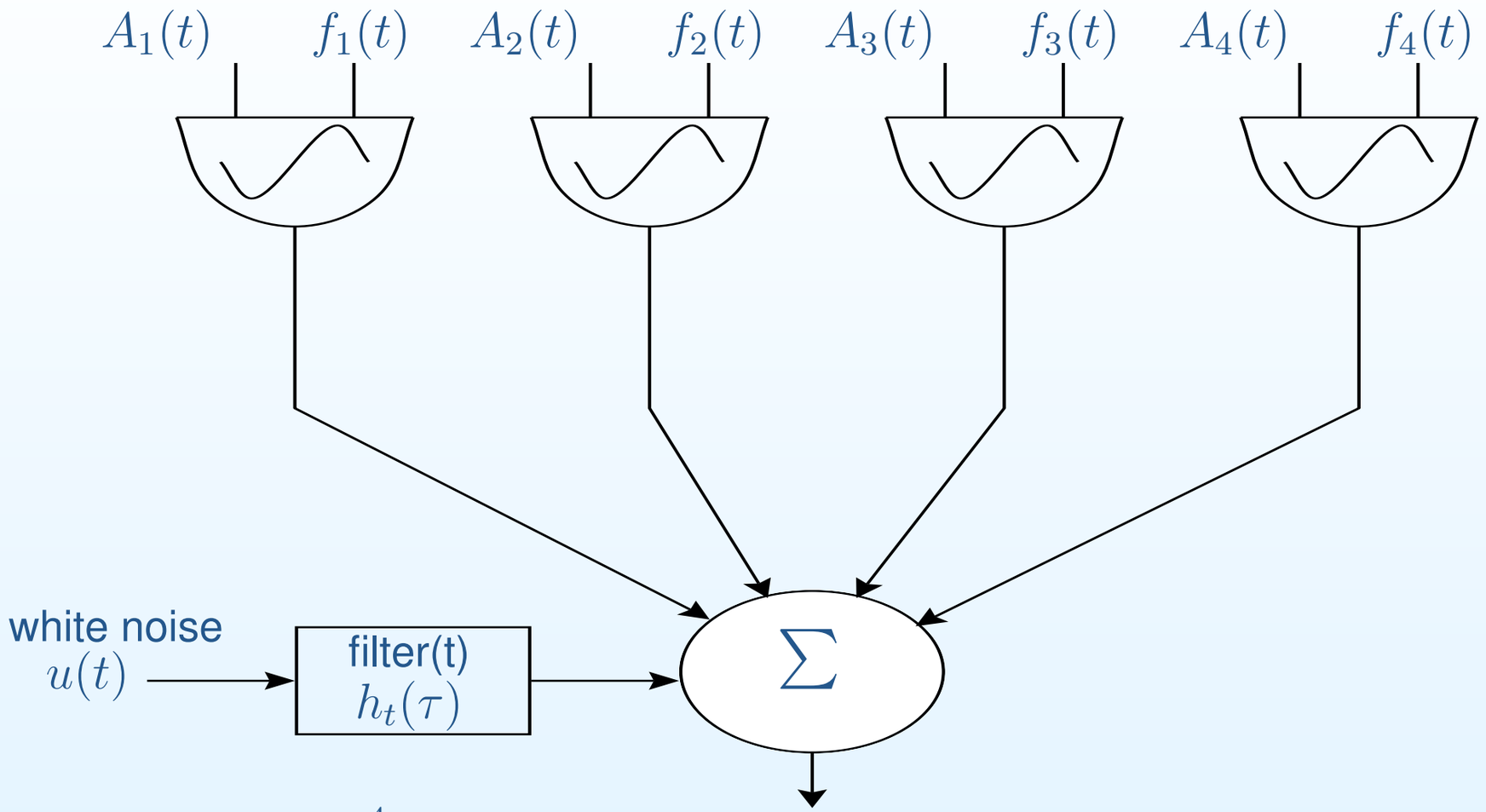
# Example Spectral Trajectories







# Parametric Spectral Modeling (1989)




$$y(t) = \sum_{i=1}^{4} A_i(t) \cos\left[\int_0^t \omega_i(t)dt + \phi_i(0)\right] + (h_t * u)(t)$$



# Sines + Noise Sound Examples

Xavier Serra 1989 thesis demos (Sines + Noise signal modeling)

- Piano
  - Original
  - Sinusoids alone
  - Residual after sinusoids removed
  - Sines + noise model
- Voice
  - Original
  - Sinusoids
  - Residual
  - Synthesis



# Musical Effects with Sines+Noise Models (Serra 1989)

- Piano Effects
  - Pitch downshift one octave
  - Pitch flattened
  - Varying partial stretching
- Voice Effects
  - Frequency-scale by 0.6
  - Frequency-scale by 0.4 and stretch partials
  - Variable time-scaling, deterministic to stochastic



# Cross-Synthesis with Sines+Noise Models (Serra 1989)

- Voice “modulator”

- Creaking ship’s mast “carrier”
- Voice-modulated creaking mast
- Same with modified spectral envelopes



# Sines + Transients Sound Examples (Serra 1989)

In this simple technique, the sinusoidal sum is phase-matched at the cross-over point only (with no cross-fade).

- Marimba
  - Original
  - Sinusoidal model
  - Original attack, followed by sinusoidal model
- Piano
  - Original
  - Sinusoidal model
  - Original attack, followed by sinusoidal model



# Multiresolution Sines + Noise + Transients (Levine 1998)

## Why Model Transients Separately?

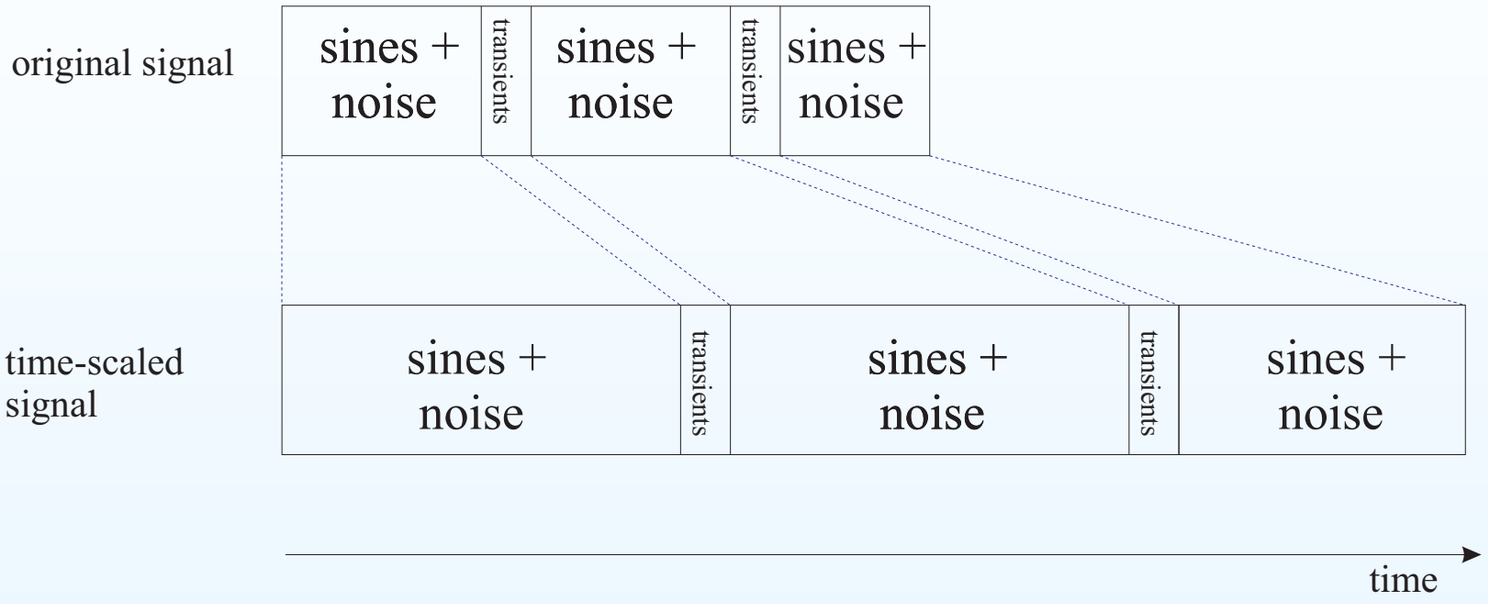
- Sinusoids efficiently model spectral *peaks* over time
- Filtered noise efficiently models spectral *residual* vs. t
- Neither is good for *abrupt transients* in the waveform
- Phase-matched oscillators are expensive
- More efficient to switch to a *transient model* during transients
- Need sinusoidal *phase matching* at the switching times

## Transient models:

- Original waveform slice (1988)
- Wavelet expansion (Ali 1996)
- MPEG-2 AAC (with short window) (Levine 1998)
- Frequency-domain LPC
  (time-domain amplitude envelope) (Verma 2000)



# Time Scale Modification of Sines + Noise + Transients Models

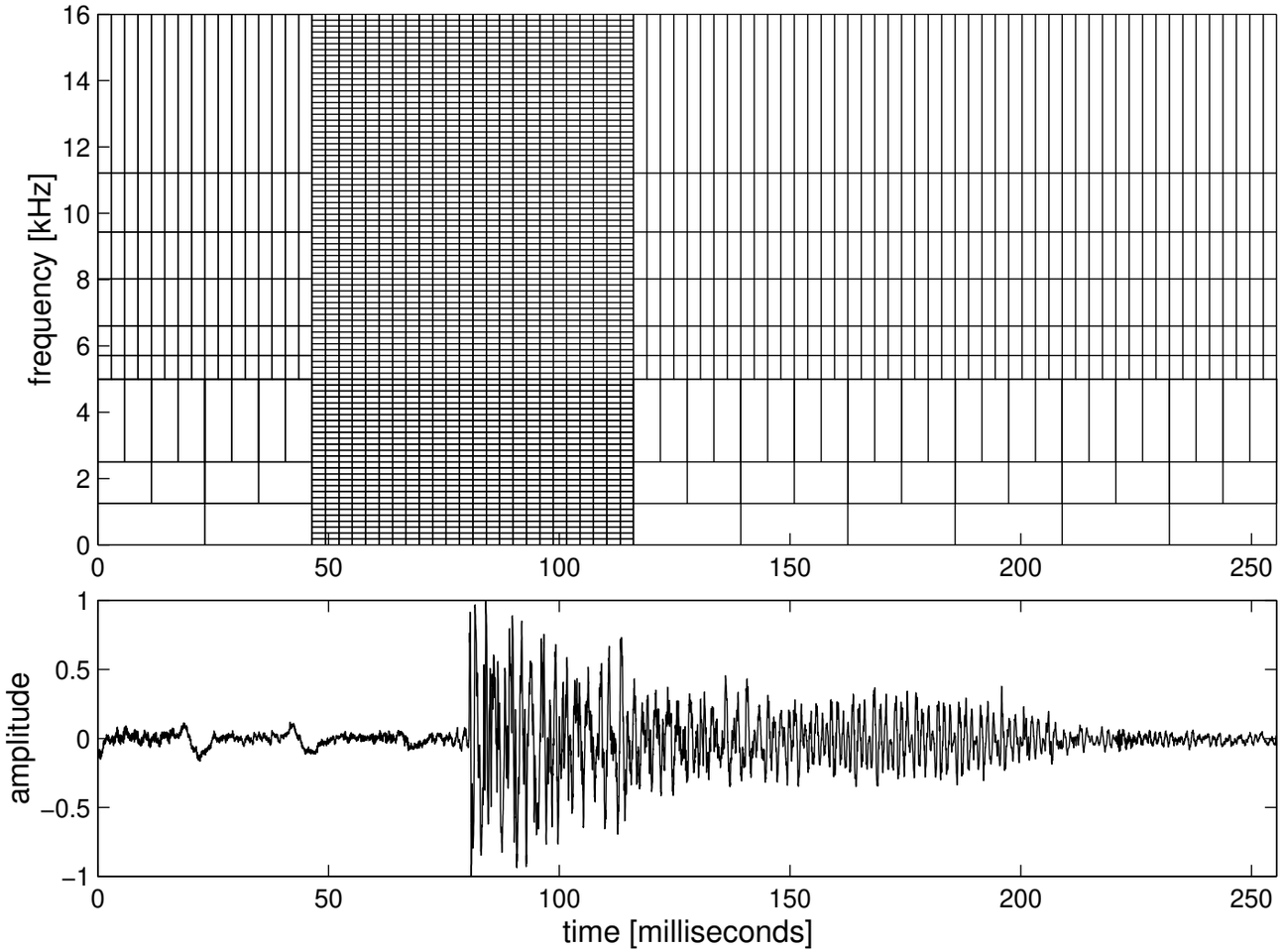



Time-Scale Modification (TSM) becomes *well defined*:

- Transients are *translated* in time
- Sinusoidal envelopes are *scaled* in time
- Noise-filter envelopes also *scaled* in time
- Dual of TSM is *frequency scaling*



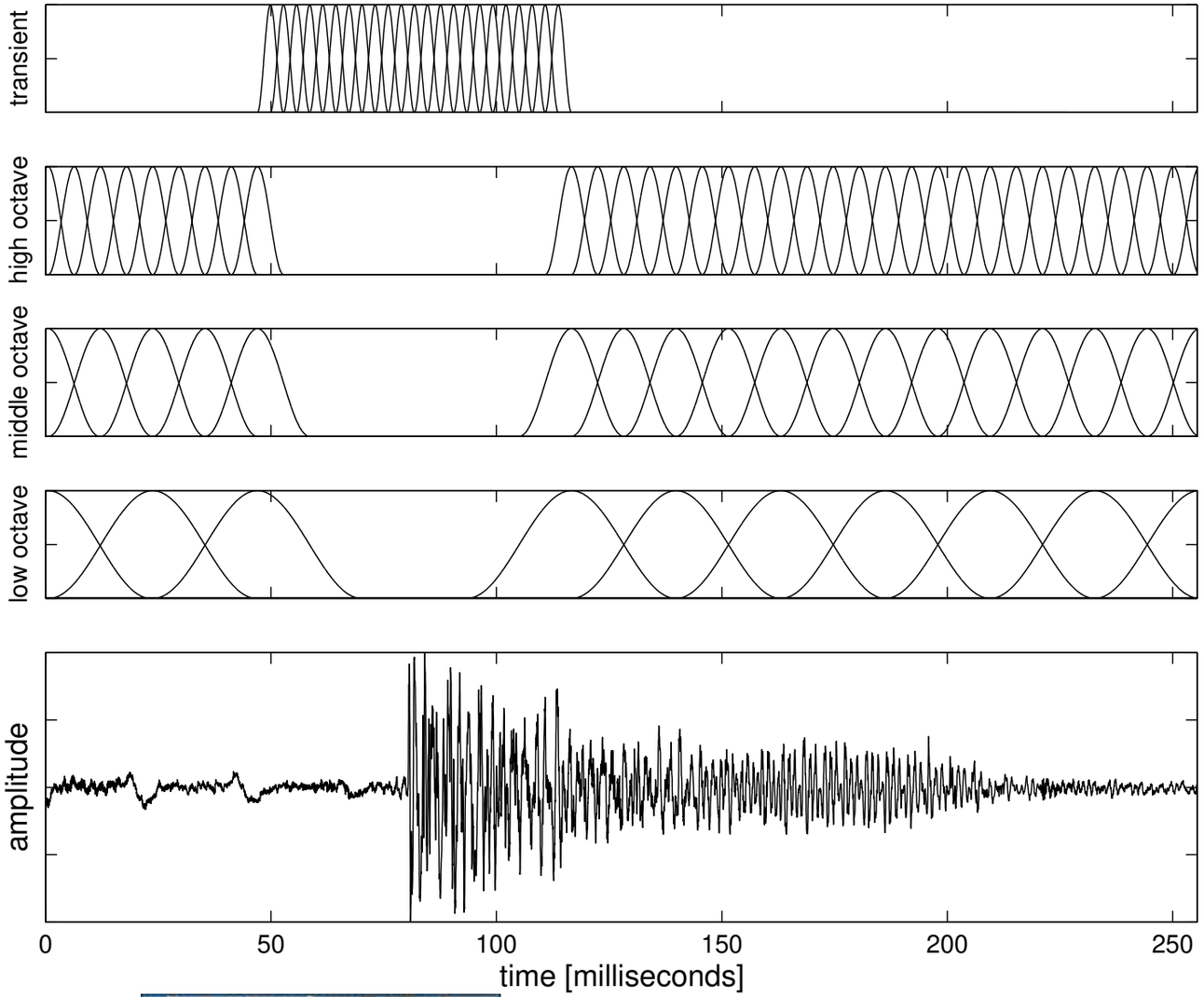
# Sines + Noise + Transients Time-Frequency Map




(Levine 1998)

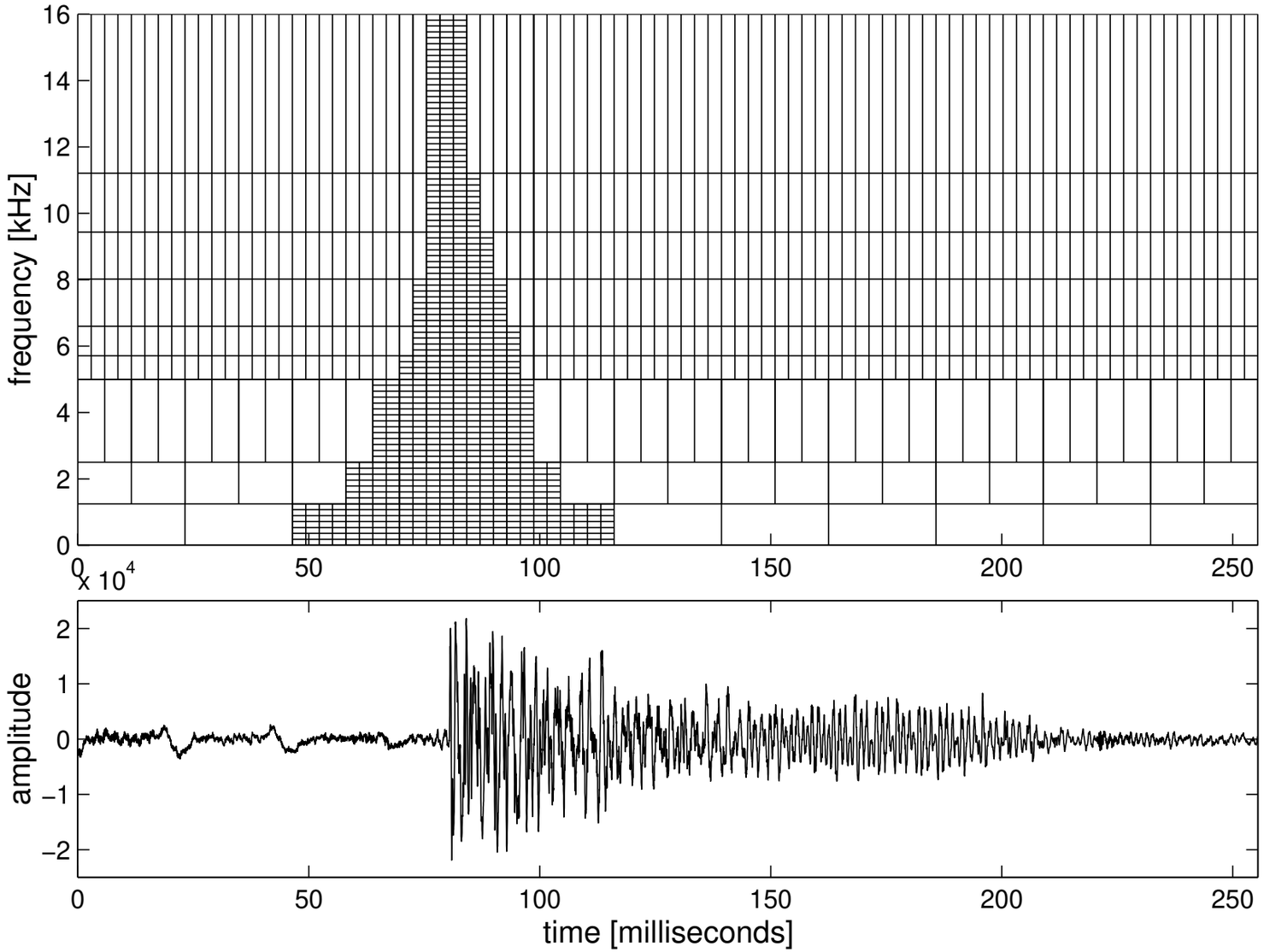
# Corresponding Analysis Windows





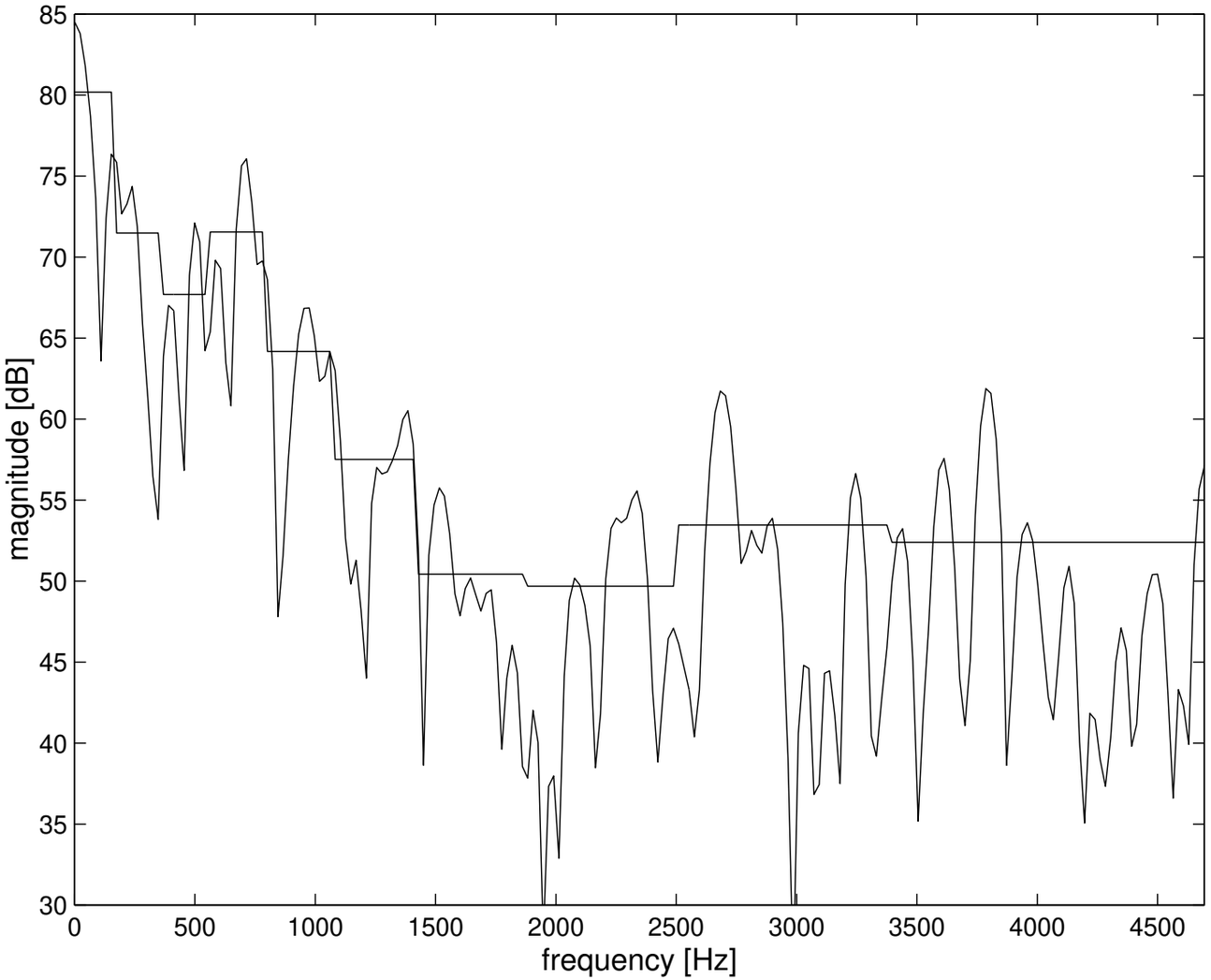


# Quasi-Constant-Q (Wavelet) Time-Frequency Map



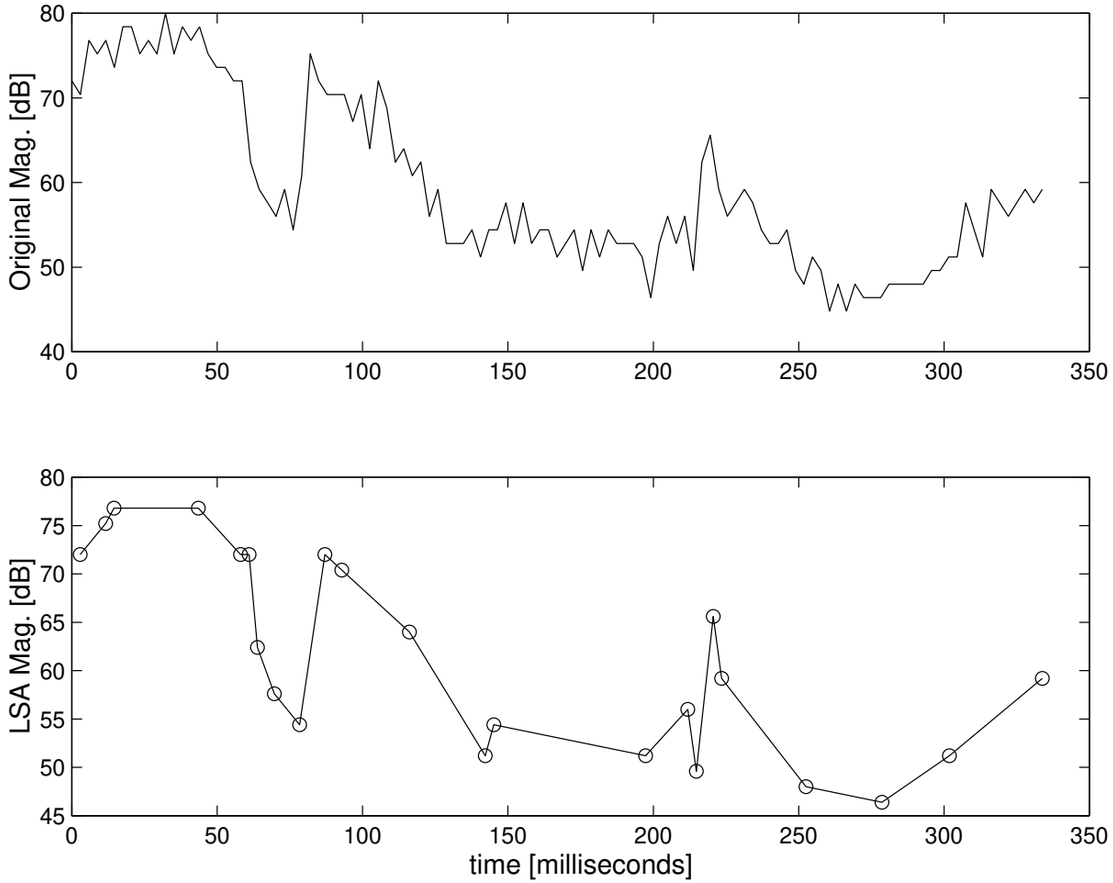


# Bark-Band Noise Modeling (Levine 1998)





# Amplitude Envelope for One Noise Band




For more information, see Scott Levine's thesis.[1]

[1] `http://ccrma.stanford.edu/~scottl/thesis.html`



# Sines + Noise + Transients Sound Examples

Scott Levine Thesis Demos (Sines + Noise + Transients at 32 kbps)
(`http://ccrma.stanford.edu/~scottl/thesis.html`)

**"It Takes Two" by Rob Base & DJ E-Z Rock**

- Original
- MPEG-AAC at 32 kbps
- Sines+transients+noise at 32 kbps

- Multiresolution sinusoids
- Residual Bark-band noise
- Transform-coded transients (AAC)
- Bark-band noise above 5 kHz



# Time Scale Modification using Sines + Noise + Transients

Scott Levine Thesis Demos (Sines + Noise + Transients at 32 kbps)
(`http://ccrma.stanford.edu/~scottl/thesis.html`)

**Time-Scale Modification** (pitch unchanged)

- S+N+T time-scale factors [2.0, 1.6, 1.2, 1.0, 0.8, 0.6, 0.5]

**S+N+T Pitch Shifting** (timing unchanged)

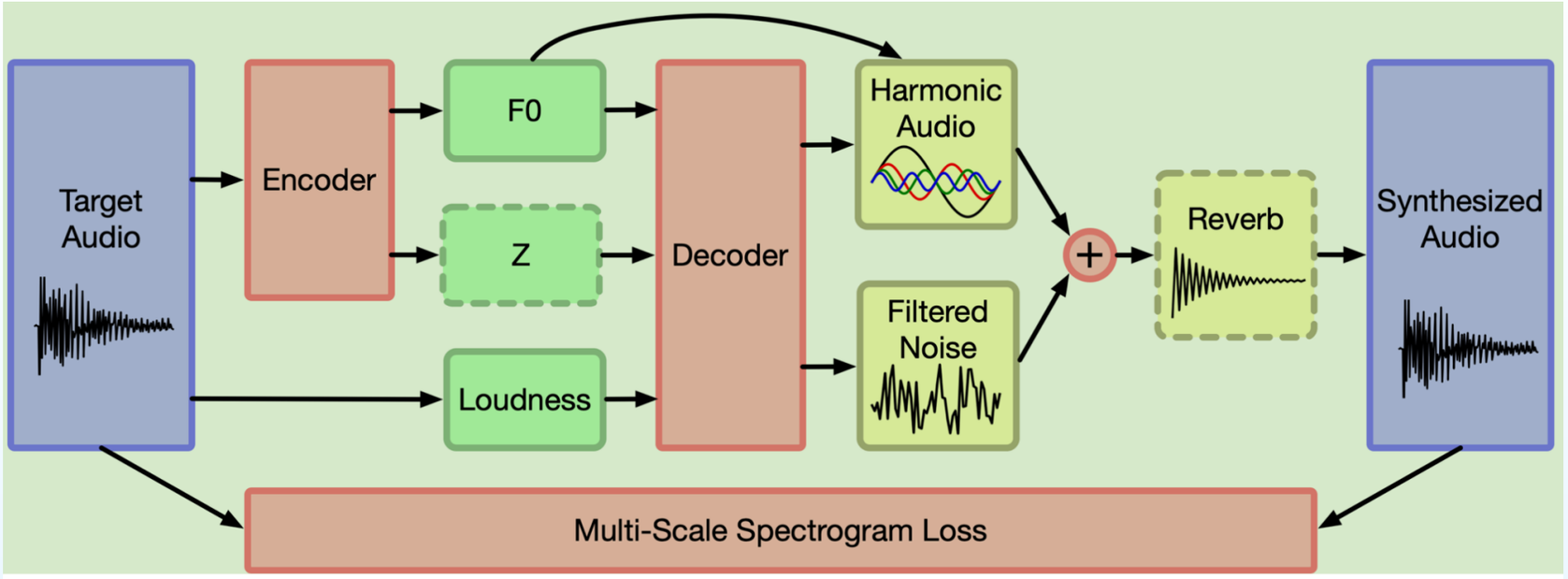
- Pitch-scale factors [0.89, 0.94, 1.00, 1.06, 1.12]



# Differentiable DSP (2019)



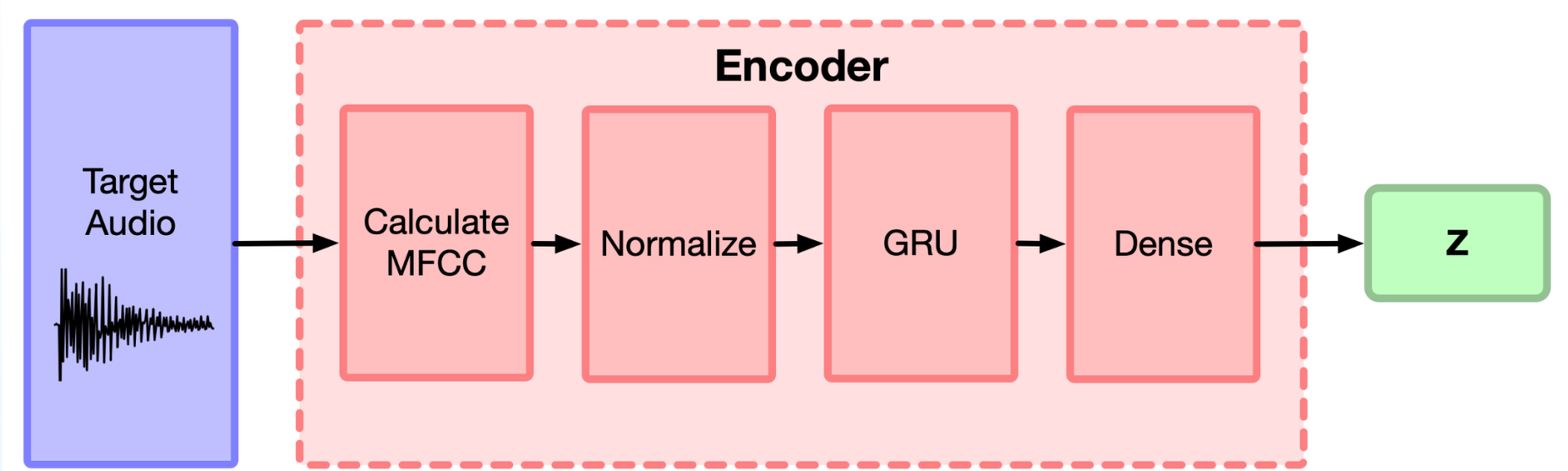
# Differentiable DSP (AI Meets Sines+Noise Synthesis




- Jesse Engel et al. at Google Magenta Group
- Neural network analysis/synthesis for *differentiable signal models*
- *Additive Synthesis* example:
  - Loudness normalized by A-weighted log-power spectrum
  - Fundamental Frequency F0 from pretrained CREPE pitch detector
  - Timbre vector Z from *autoencoder*
  - Timbre vector decodes to sinusoidal amplitude trajectories



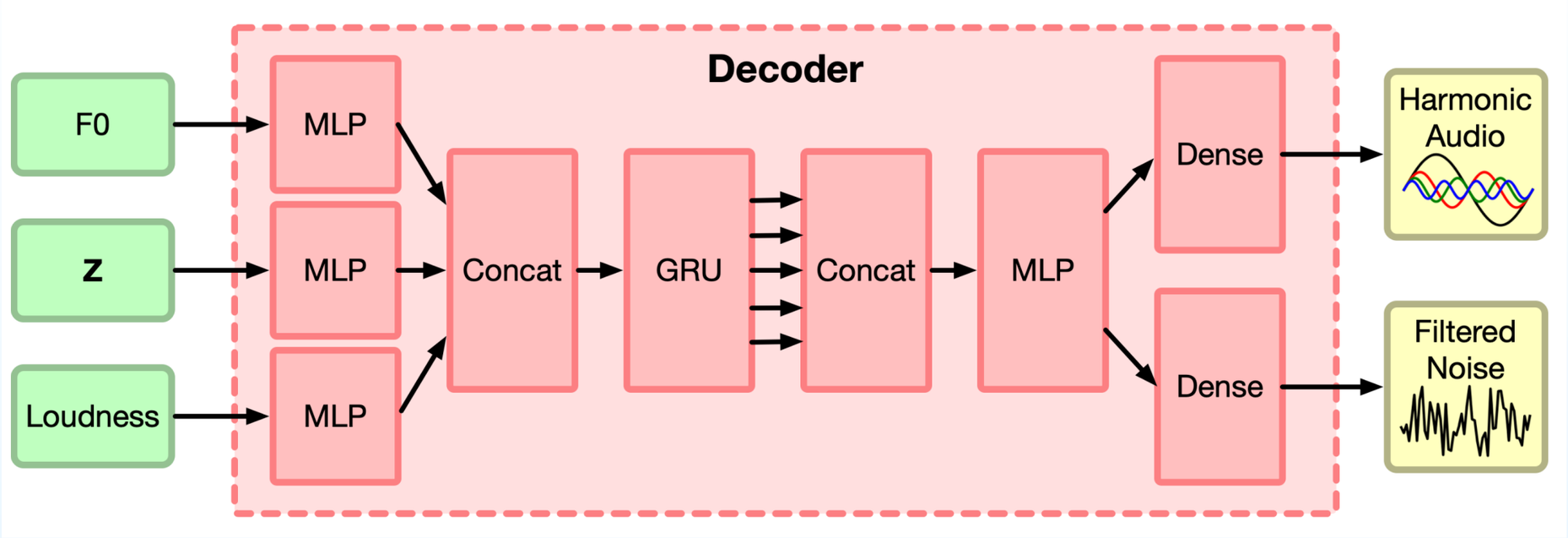
# DDSP Encoder




- Loudness and F0 of Target Audio have been normalized away
- MFCC = Mel Frequency Cepstral Coefficients
- GRU = Gated Recurrent Unit (Cho 2014) - similar to LSTM = Long/Short-Term Memory
- Dense = Fully Connected Linear Deep Neural Net (512-to-16 compression step)
- F0 and Loudness normalization leave only *timbre* to be encoded



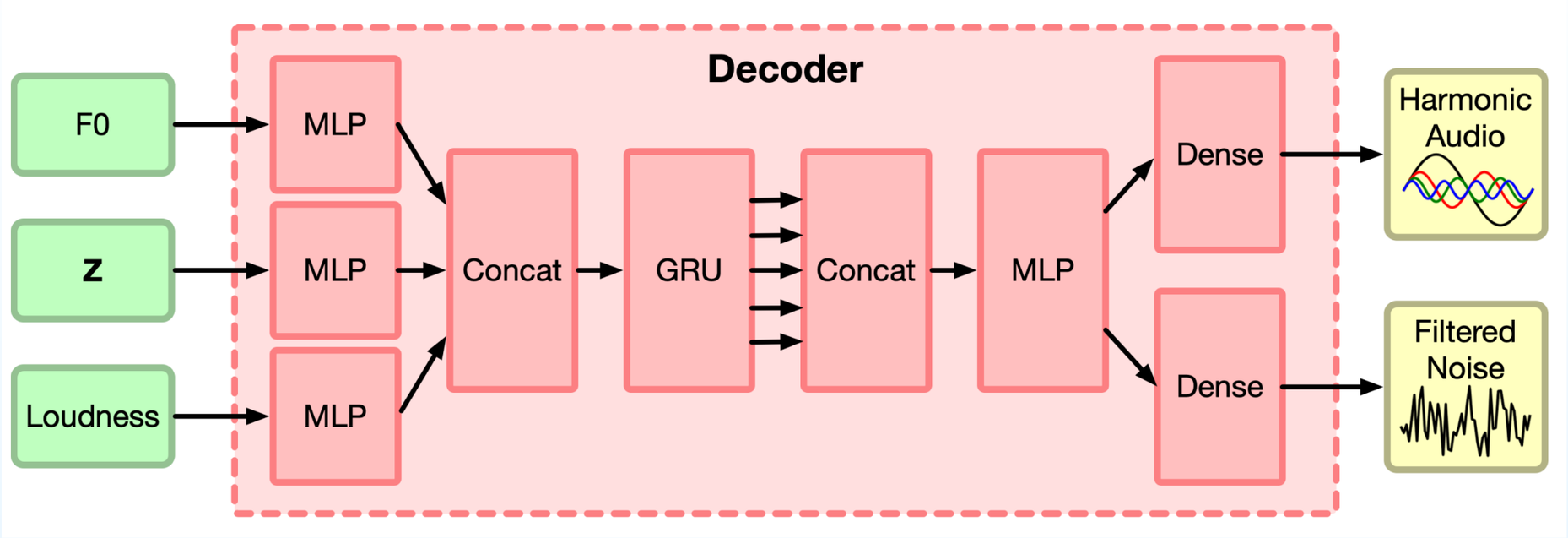
# DDSP Decoder



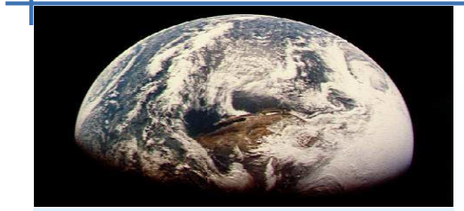

- MLP = Multi-Layer Perceptron (classical neural network)
- 250 time steps (frames) included
- Output is additive synthesis parameters (sines + filtered noise)



# DDSP MLP




- RELU = Rectified Linear Unit (half-wave rectifier)
- 3 layers and 512 Units
- Entire model is differentiable end to end, so back-propagation can optimize everything together (ADAM optimizer used)
- Optimization is generally Stochastic Gradient Descent





# Audio in Generative AI



# Recent AI Music Audio Generation Timeline

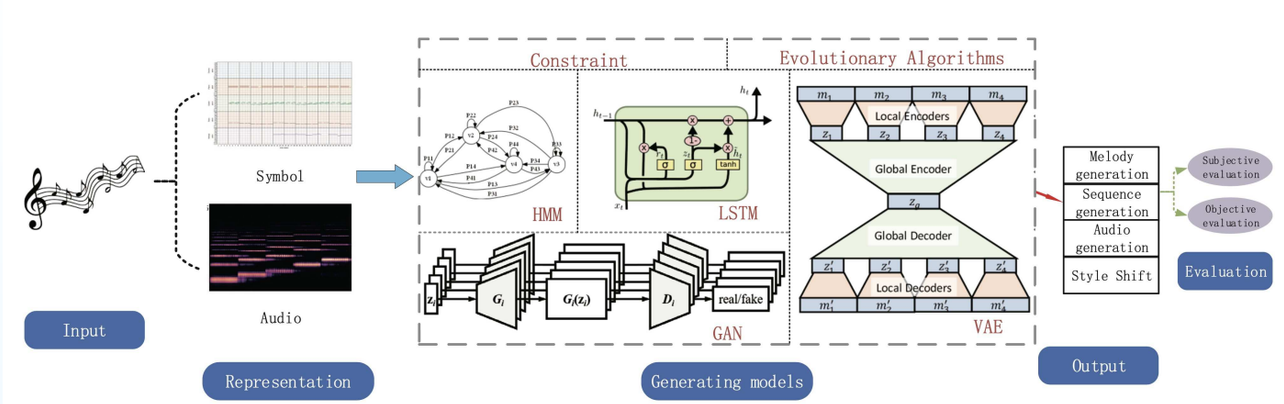


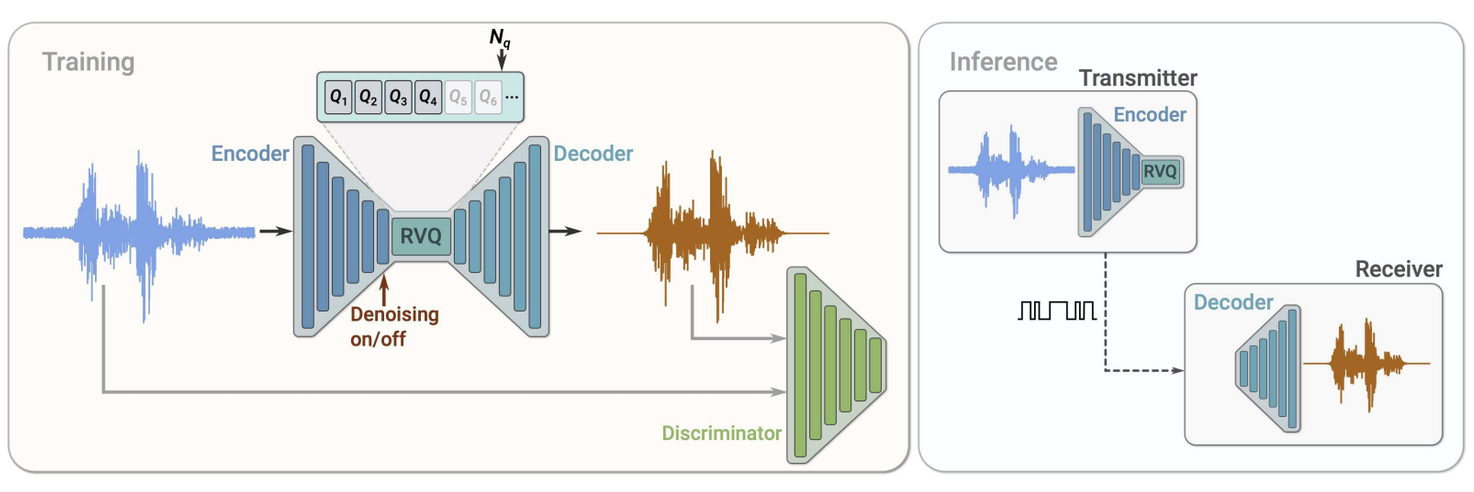

**Fig. 1**: Overview of music generation system

From [Review] below

- 2016 - WaveNet: “A Generative Model for Raw Audio”
- 2017 - SampleRNN: “Generating Albums with SampleRNN . . . ” [Dadabots]
- 2019 - MusicVAE: “A Hier. Latent Vector Model for Learning L.T. Structure in Music”
- 2020 - Jukebox: “A Generative Model for Music”
- 2022 - [Review]: “A Review of Intelligent Music Generation Systems”
- 2022 - “AudioLM: a Language Modeling Approach to Audio Generation”
- 2023 - “MusicLM: Generating Music From Text” [Jan]
- 2023 - MusicGen: “Simple and Controllable Music Generation” [Jun]



# AI Audio Codec Timeline




SoundStream: `https://arxiv.org/abs/2107.03312`

- 1984 - Vector Quantization (VQ)
- 2013 - Variational AutoEncoder (VAE)
- 2018 - VQ-VAE: “Neural Discrete Representation Learning”
- 2021 - “SoundStream: An End-to-End Neural Audio Codec”
- 2022 - EnCodec: “High Fidelity Neural Audio Compression”
- 2023 - “SoundStorm: Efficient Parallel Audio Generation” [May]
- 2023 - Descript: “High-Fidelity Audio Compression with Improved RVQGAN” [Jun]

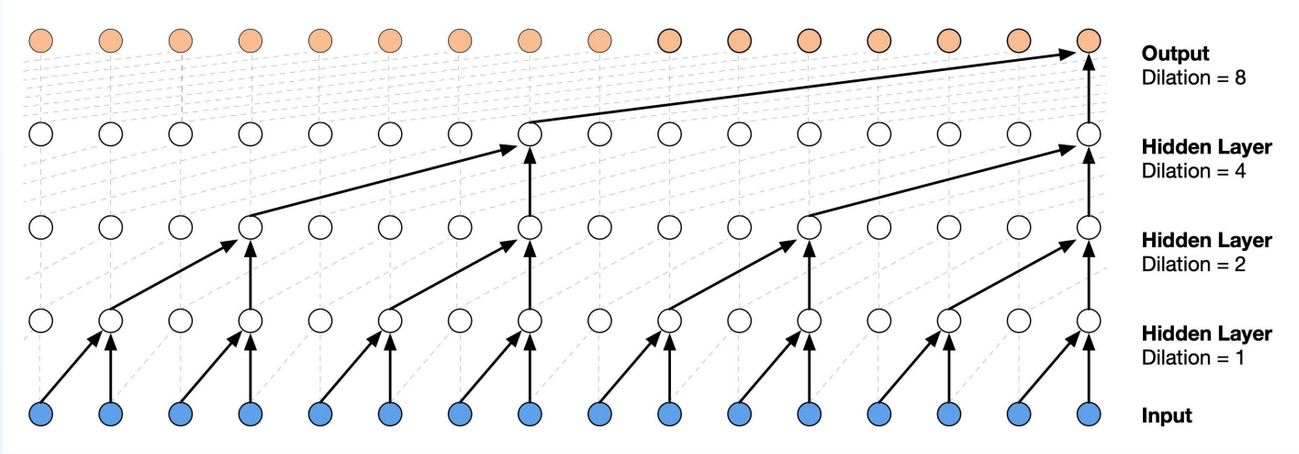


# Will Spectral Modeling Continue?



# WaveNet (van den Oord et al., 2016) "A Generative Model for Raw Audio"

WaveNet achieved superior text-to-speech (TTS) by predicting *time samples* autoregressively (no spectral representations)



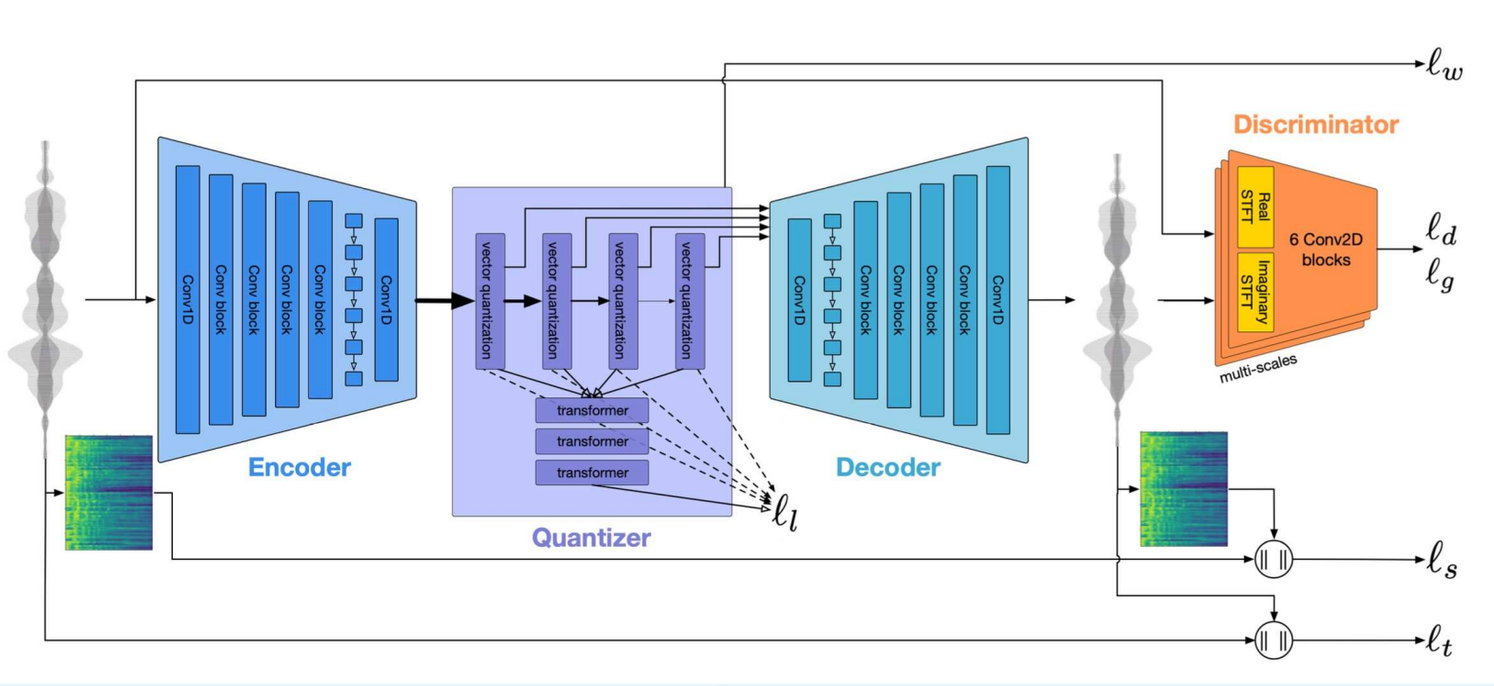

Training WaveNet's nonlinear (mu-law) sample predictor.

"Traditionally, speech recognition research has largely focused on using log mel-filterbank energies or mel-frequency cepstral coefficients (MFCCs), but has been moving to **raw audio** recently."

# Descript (2023) “High-Fidelity Audio Compression ...”

Based on **SoundStream** (2021), **EnCodec** (2022), and others,

**Descript** (2023) achieves state-of-the-art performance on benchmarks for AI audio codecs:




EnCodec

- Time-domain *convolutional encoder-decoder* architecture
- Time-domain *multi-period discriminator* loss
- Frequency-domain discriminator-loss based on *complex multiresolution STFT*
- Frequency-domain *multiresolution mel-spectrogram reconstruction loss* (L1 norm)

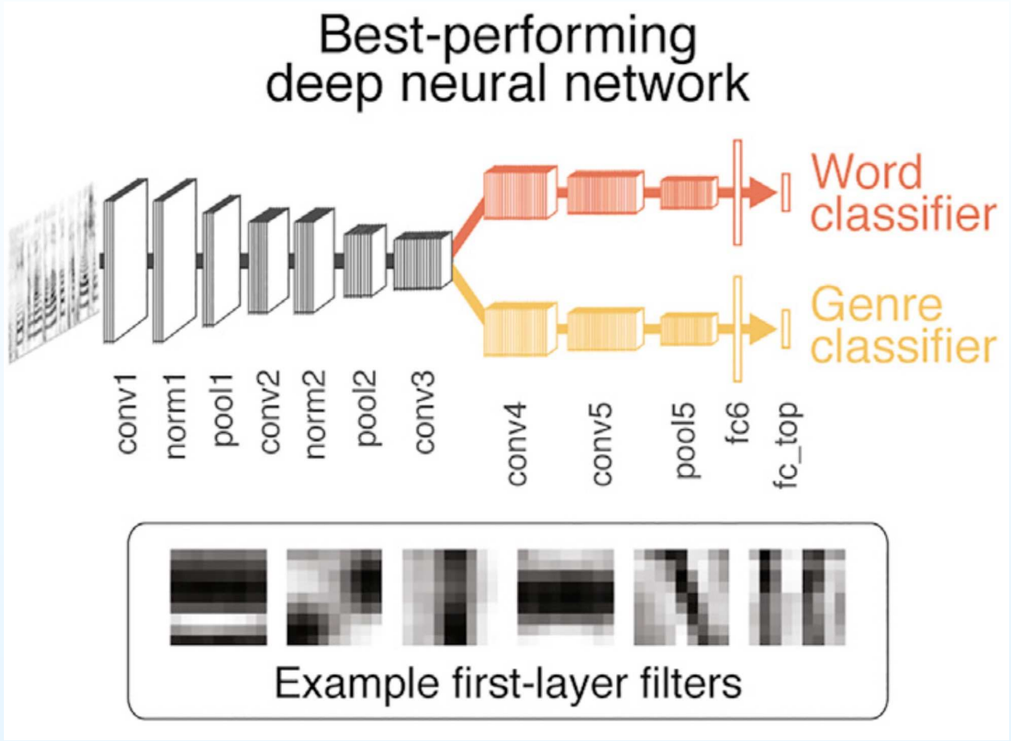


# Spectral Methods in Recent AI Audio Systems

- **SoundStream** (2021), **EnCodec** (2022), and **Descript** (2023) show a progression from end-to-end learning (**WaveNet** 2016) to the use of *multiresolution spectral reconstruction and adversarial losses*
  - Learning such auditory loss functions end-to-end is *much* more work
  - The audio coder/decoder itself is learned end-to-end: "neural concatenative synthesis"

- Spectra are also pushing back into the *decoder:*
  - **ISTFTNet** (2023): Replaces last two upsample blocks of **HiFi-GAN** with *iSTFT*
  - **Vocos** (2023): Replaces *whole decoder* by iSTFT $\Rightarrow$ model = STFT coefficients $\Rightarrow$ Matches SOTA using an *order of magnitude less computing*

## McDermott Lab Example: Kell et al., Neuron 2018




- *Cochleagram* presented as an image input to the convolutional neural network (CNN)
- For word recognition and music genre classification, this 12-layer network emerged as best (out of 180 tried)
- The 1st 7 *shared* layers were found to perform comparably with separate 12-layer networks
- Performs at human level, with similar errors
- Predicts fMRI responses in the audio cortex
- Outperforms previous spectrotemporal filter models of the audio cortex
- Cochleagram required for predicting human responses
- Perhaps the cochleagram can be replaced by vastly more natural data and training (evolution-equivalent)



# F0 Estimation Reinvents Auditory Filter Bank

## Verma and Schafer, Interspeech 2016

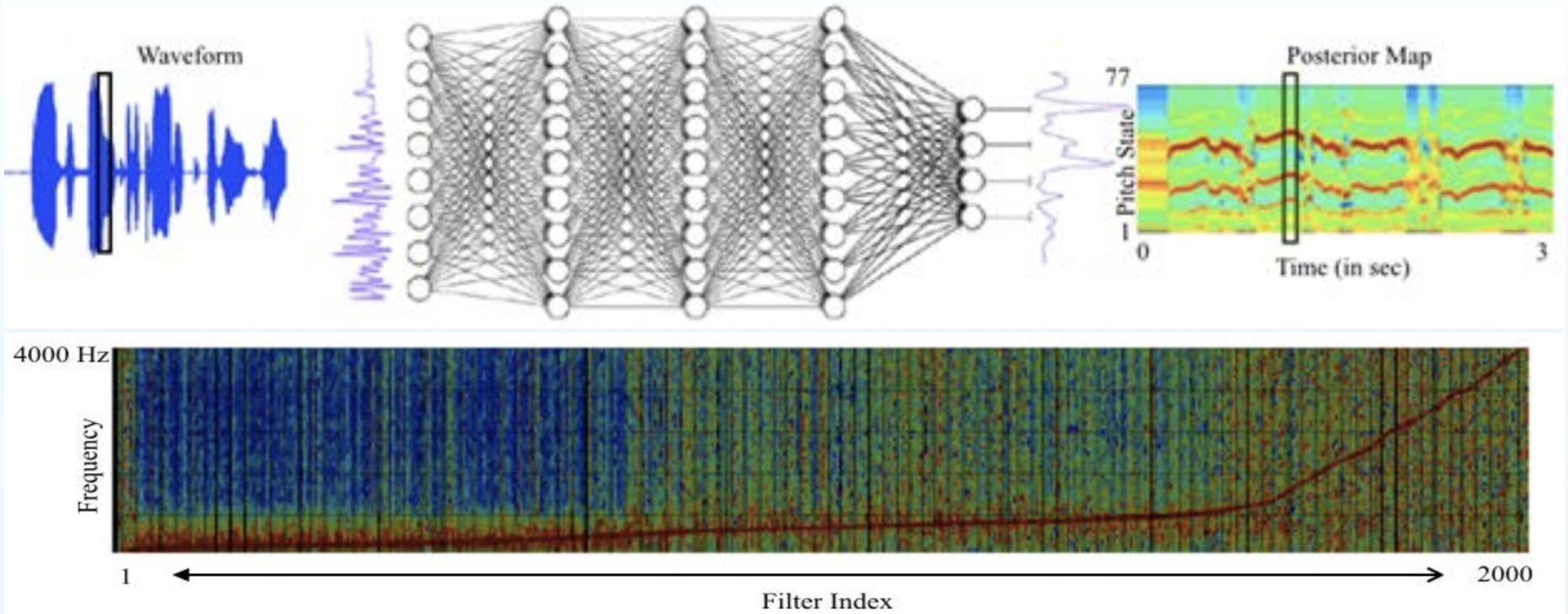



Figure 4: *Frequency response of the learned filters in the first layer sorted according to the highest peak for TIMIT. Red denotes high values whereas blue represents smaller value.*

- Audio filter bank *learned* in the first layer for the F0-estimation task
- Filter bands more dense in the F0 range
- To do: Replace or prepend first layer with a *pre-structured auditory filter bank* having a *differentiable and convex* parameterization, allowing it to be *data* and *task adaptive*



# Spectral Representations Continue to be Useful

- Models of hearing (e.g., *Josh McDermott*'s Computational Cognitive Neuroscience lab)
- High-quality audio compression (e.g., **MPEG AAC** (`.m4a`))
- *Reconstruction loss* for audio models and tasks (e.g., **Descript 2023**)
- *Adversarial loss* for audio perception (e.g., **Descript 2023**)
- Faster vocoders (e.g., **Vocos** 2023)
- Intuitive and far more efficient targets for *reverse diffusion* (e.g., **Riffusion** 2022)
- Audio generation *feature-based controls* (e.g., **SingSong** 2023)
- *Human-editable* outputs (e.g., **Anticipatory Music Transformer** 2023)

**End-to-End** $\rightarrow$ **Embedded Known DSP** is a natural progression, especially for smaller systems

> Huge *end-to-end systems* trained on "infinite" data are great for establishing state-of-the-art performance, but then we can try to *win back territory* from opaque neural nets using *far more efficient and precise processing* (ideally differentiable), while maintaining comparable quality.



# Advantages of Spectral Representations

Spectral representations provide

- "Structural Priors" (Inductive Bias) aligned to **human hearing**
  (forcing synthesis models to the distribution of natural sounds for humans)
- "Human-Centered Loss Functions" (minimize the errors that humans hear most)

These contributions give reduced

- model size,
- training time,
- data requirements,
- computation,
- fossil fuel consumption (:D)

**Common theme:** *Keeping It Human*

*Maybe spectral representations no longer needed after the AI Apocolypse?*



# Key Takeaways

- Spectrum analysis “hardware” evolved in the human ear to extend its frequency response and sensitivity
- Time-frequency distributions are fundamental to human audio/music perception and appreciation
- Musical instruments evolved accordingly
- Audio compression evolved accordingly
- AI can reinvent spectral processing, or we can provide it, saving training
  - “Neural concatenative synthesis” needs frequent phase matching, so time-domain and frequency-domain models are not that different
  - Audio loss functions still employ spectral methods
  - Differentiable DSP adds trainable known structure that will surely keep growing
  - Constraining AI to human ears (e.g., cochleagram front ends) helps to model human audio perception