

Reverse Engineering Memoryless Distortion Effects with Differentiable Waveshapers

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Overview

Distortion modelling:

- Black-, Grey- and White-box modelling
- Wiener-Hammerstein models

Differentiable Digital Signal Processing

Differentiable Waveshapers

- Sumtanh family
- Powtanh family

Objective Evaluation & Listening Test

Distortion Effect Modelling

White-box Models:

- Based on complete knowledge of the system
- Ordinary/partial differential equations to describe behaviour
- Numerical methods to solve them in the continuous or discrete domain

Black-box Models:

- No prior knowledge about the system
- Only input-output measurements
- Includes end-to-end neural network models

Grey-box Models:

- Partial theoretical structure (Block-oriented model) + Data
- Reduce prior knowledge necessary to model device
- Maintain a degree of interpretability

Wiener-Hammerstein Grey-box Model



Differentiable Digital Signal Processing

- Common DSP modules implemented in a differentiable framework (e.g., Tensorflow or Pytorch)
- Auto differentiation allows for these modules to be implemented in or controlled by neural networks due to their ability to backpropagate gradients

Proposed Wiener-Hammerstein Model



Pre-emphasis and De-emphasis topology

- "Graphic" FIR EQ
- Attenuations specified at semi-octave bands + low and high shelves
- Transfer curve interpolated between these values
- Windowing + spectral sampling method for inversion to time domain



Differentiable Waveshapers



Sumtanh nonlinearity

 $f(x) = a_1 \tanh(x) + a_2 \tanh(2x) + \dots$ $a_{n-1} \tanh((n-1)x) + a_n \tanh(nx)$

Powtanh nonlinearity $f(x) = a_1 \tanh(x) + a_2 \tanh(x^2) + \dots$ $a_{n-1} \tanh(x^{n-1}) + a_n \tanh(x^n)$

Sumtanh family

$$f(x) = a_1 \tanh(x) + a_2 \tanh(2x) + \ldots + a_n \tanh(nx)$$
$$a_0 = -\sum_{c=1}^n a_c \tanh(c \times b_{DC})$$



Powtanh family

$$f(x) = a_1 \tanh(x) + a_2 \tanh(x^2) + \ldots + a_n \tanh(x^n)$$



Evaluation - Reverse Engineering Distortion Effects

- Stochastic gradient descent updates the W-H model parameters to fit a dry/wet audio pair
- Parameters include:
 - Attenuations for pre-emphasis and de-emphasis filters
 - \circ Gain
 - All coefficients in the waveshaper
 - \circ Volume
- Loss is calculated by passing a dry audio sample through the estimated W-H model and measuring the multiscale spectrogram loss between the estimated and target audio

Results

Table 3: Mean multiscale spectrogram loss of the waveshapers evaluated across pedals

Waveshaper	RAT	MGS	VTB	Total
Powtanh	1.321	0.559	2.117	1.332
Sumtanh	1.321	0.573	2.400	1.431
Fourier	1.588	0.603	2.686	1.625
Legendre	1.703	0.640	2.893	1.746
Tanh	1.353	0.597	2.478	1.476

Designer	Plugin	Emulation of	Id
Audified	Multidrive Pedal Pro	ProCo Rat	RAT
Mercuriall	Greed Smasher	Mesa/Boogie Grid Slammer	MGS
Analog Obsession	Zupaa	Vox Tone Bender	VTB

Results



Fig. 2: Example of estimated waveforms for each waveshaping model on a VTB example

Results



Future Work

- Implement explicit antialiasing
- Model hysteresis for distortion effects with memory
- Implement signal-dependent conditioning for full effect modelling



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Appendix - Example Legendre Model

- Complete and orthogonal polynomials (ortho on [-1,1])
- System learns weighted sum of first N polynomials
- Signal normalized to [-0.9,0.9] before waveshaping to avoid overshoot





Appendix - Example Legendre Model



Appendix - Example Fourier Model

- Complete and orthogonal sines and cosines (ortho on [-π,π])
- System learns weighted sum of first N sinusoids
- Signal normalized to [-0.9π,0.9π] before waveshaping to avoid overshoot/zeroing





Appendix - Example Fourier Model

