

***Ph.D. Thesis Proposal***

# Automatic Construction of Synthetic Musical Instruments and Performers

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**Carnegie Mellon University**

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# Thesis Committee

- **Roger B. Dannenberg, *Chair***
- **Michael S. Lewicki**
- **Richard M. Stern**
- **David Wessel (UC Berkeley)**

# Roadmap

- **Introduction**
- **System Structure**
- **Main Modules**
  - **Audio Alignment and Segmentation**
  - **Instrument Model**
  - **Performance Model**
- **Schedule**
- **Conclusion**

# Introduction

- **Define thesis topic**
- **Thesis statement**
- **Start with modeling *the trumpet* for *classical music***
- **Contributions of the thesis**
- **Criteria for success**

# Topic Definition

- ***Title***

**Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Framework that builds music synthesis**

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**Automatic Construction of Synthetic Musical Instruments and Performers**

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- **Framework that builds music synthesis**
- **Automatic construction**

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# Topic Definition

- ***Title***

**Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Framework that builds music synthesis**
  - High quality
  - High performance
  - Capable of modeling different instruments
  - Capable of modeling different music styles

# Topic Definition

- ***Title***

## **Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Automatic construction**

- **Use machine learning techniques**
- **Learn from performance examples**
- **Constructs instrument model and performance model**

# Topic Definition

- ***Title***

## **Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Instrument model**

- **Similar to traditional concept of *synthesis***
- **Input: control signals**
- **Output: synthesized sound samples**

# Topic Definition

- ***Title***

## **Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Performance model**

- **Generating appropriate control signals from music context is crucial**
- **Drives instrument model**
- **Input: digital score (music notation)**
- **Output: control signals**

# Topic Definition

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**Automatic Construction of Synthetic Musical Instruments and Performers**

- ***Meaning***

- **Framework that builds music synthesis**
- **Automatic construction**
- **Instrument model**
- **Performance model**

# Thesis Statement

- **To create a system framework that can automatically create high-quality musical instrument synthesis by using machine-learning techniques to construct the instrument model and the performance model by learning from the performance examples (acoustic recordings and their corresponding scores).**

# Start with Modeling...

- **Musical Instrument:**
  - Trumpet
- **Music Style:**
  - Classical Music

# Reasons for Modeling the Trumpet (1)

- **Most wind instrument synthesizers do not sound realistic**
  - **Conflict between:**
    - **Working mechanisms of wind instruments**
      - Driven by continuous energy exerted by player
      - Continuous control drives sound production
    - **Basic structure of synthesizers**
      - Mostly sampling-based
      - Based on single, isolated notes
      - Do not offer a wide range of control



# Reasons for Modeling the Trumpet (2)

- **Previous research**
  - **By Dannenberg and Derenyi (1998)**
  - **Similar scheme**
  - **Produces convincing trumpet sound**

# Reasons for Modeling Classical Music

- **Characteristics of classical music**
  - “Purer” playing style
  - More faithful to the score
  - Fewer articulation effects
- **Characteristics of non-classical music**
  - Significant inharmonic & transient sounds
  - Need to model noise with a residual model


# Contributions of the thesis

- **Use machine learning techniques**
- **Automatically create high-quality synthesis**
- **The problem of control**
  - **Problems of note-oriented synthesis**
  - **Problems of physical models**
  - **This approach simplifies the problem**

# Criteria for success

- **Minimum requirement**
  - **Design, implement & test basic framework**
  - **Being able to synthesize realistic trumpet performance for classical music**
  - **Automated modeling process**
  - **Tested on one or two wind instruments.**
- **Extra tasks**
  - **Extend system framework**
    - **Model different musical instruments**
    - **Model different music styles**
- **Future work**

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# System Structure

- **Synthesis process**
- **Pre-processing training data**
- **Training process for instrument model**
- **Training process for performance model**

# Synthesis Process

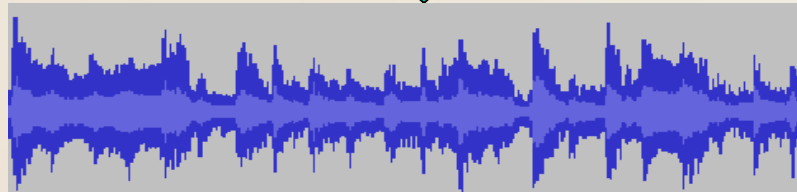


Performance  
Model

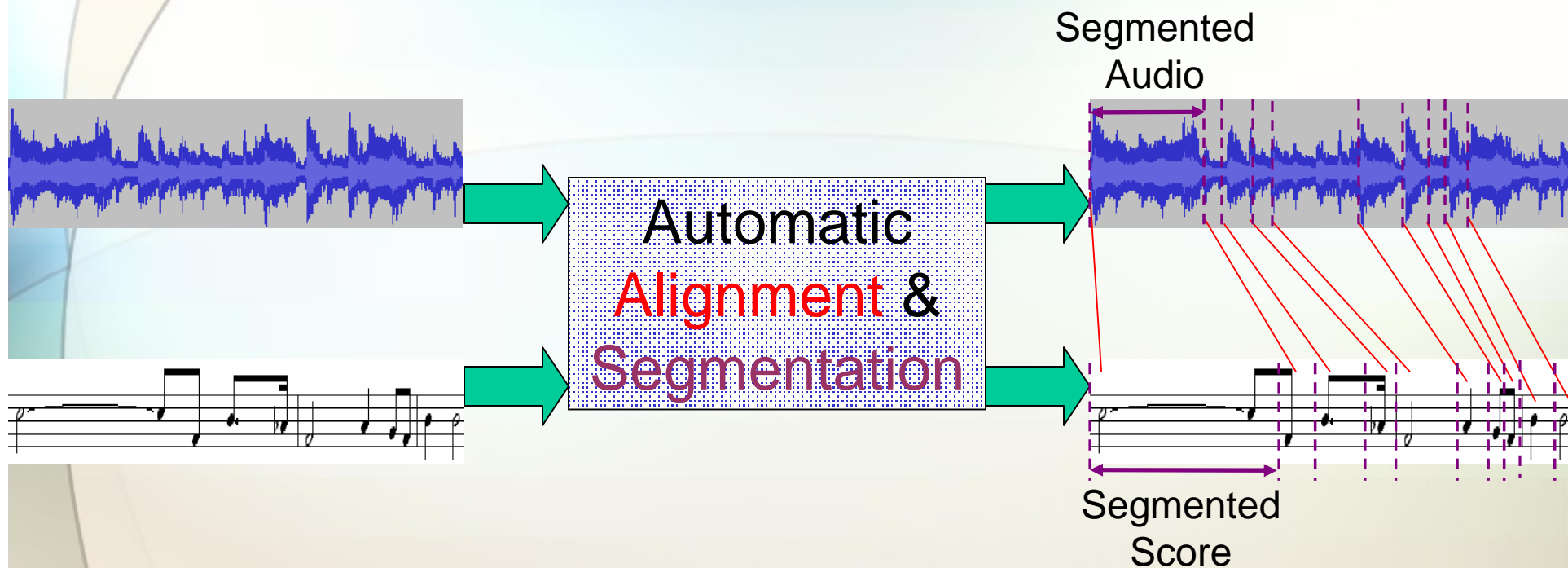


Control  
Signals

Instrument  
Model

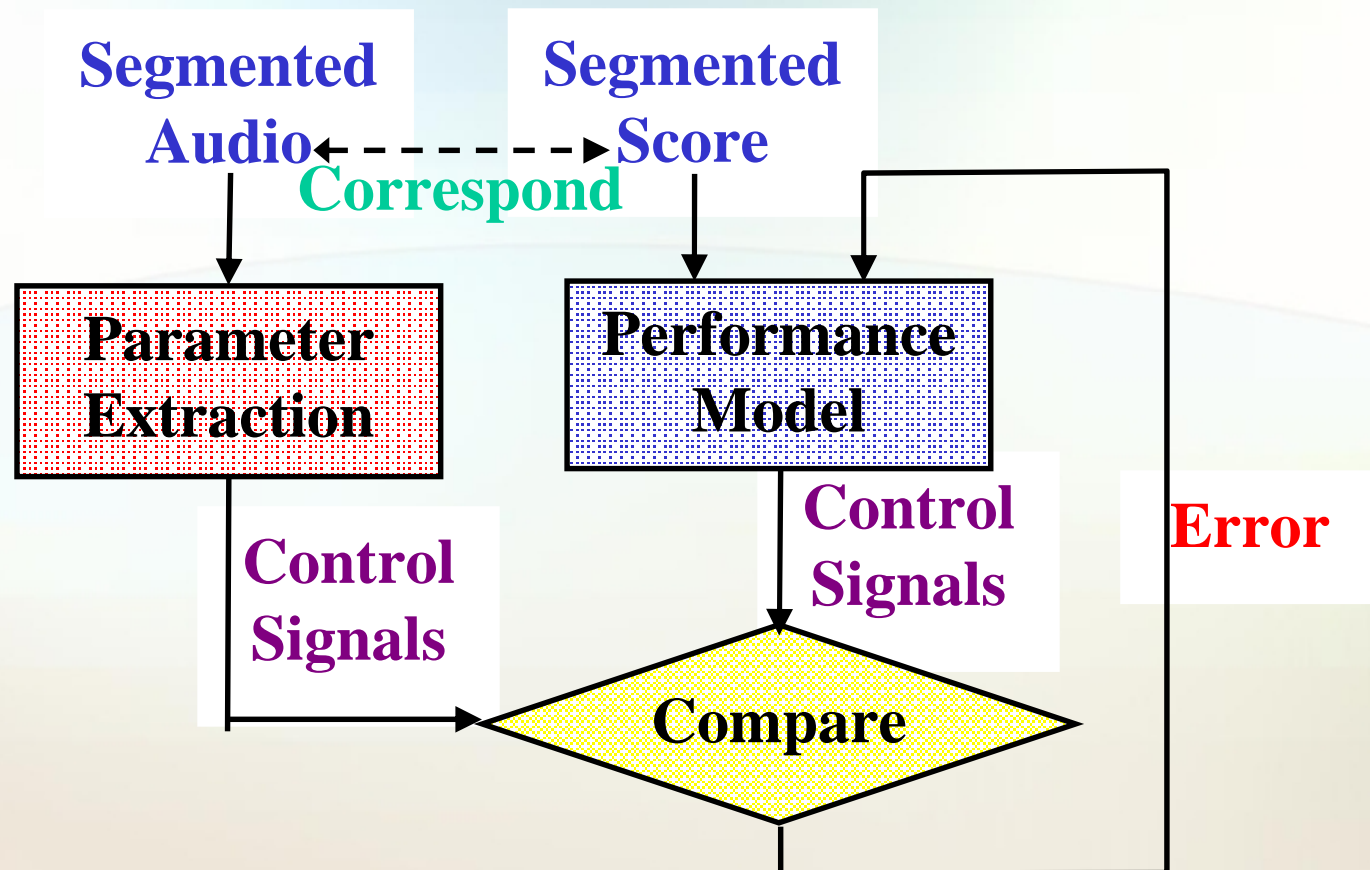


# Pre-processing training data

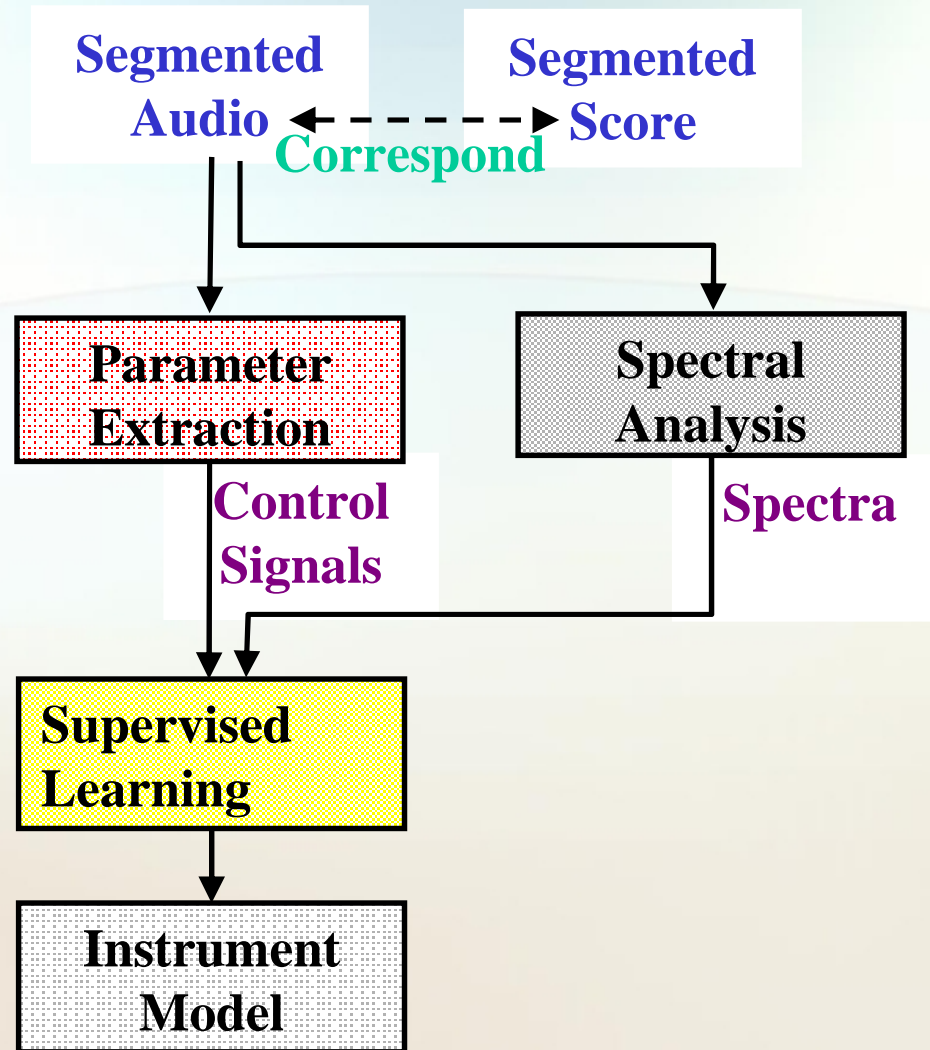






# Training the Performance Model



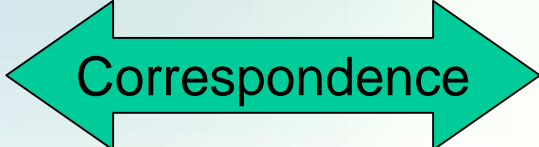
# Training the Instrument Model



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# Audio Alignment

- **Find recording**  **score**
- **Polyphonic audio alignment**
  - **Extract feature sequences from ...**
    - Acoustic recording
    - Score
  - **Find optimal alignment**
  - **Dynamic programming (DP) or Hidden Markov Model (HMM)**
  - **Satisfactory results**

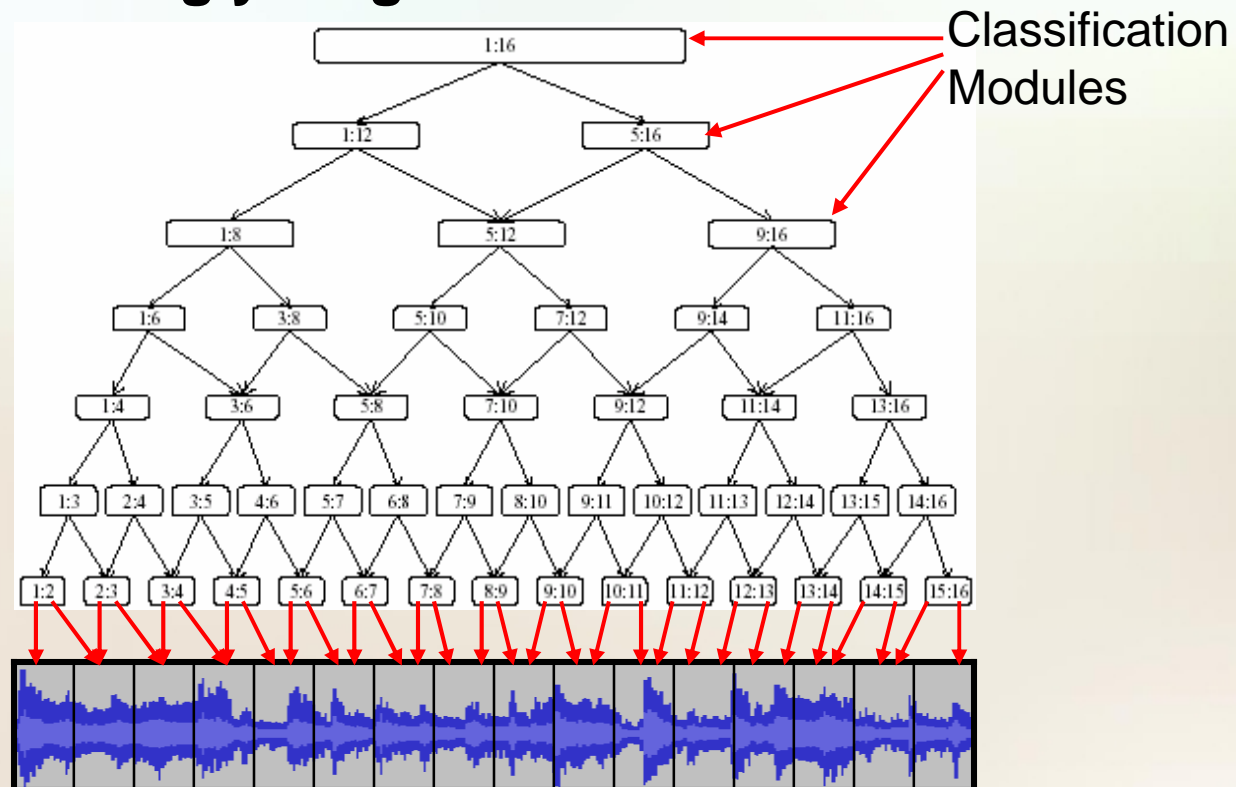
# Audio Segmentation (1)

- **Dannenbergh, et. al., (1999) early work**
  - **Define rules & thresholds**
  - **Use features: power; #peaks/period; #zero-crossings/period**
  - **Not reliable and accurate enough**
- **Precise alignment = reliable segmentation**
  - **Require higher accuracy**
  - **Need further modification**

# Audio Segmentation (2)

- **Kapanci & Pfeffer's (2004) work**

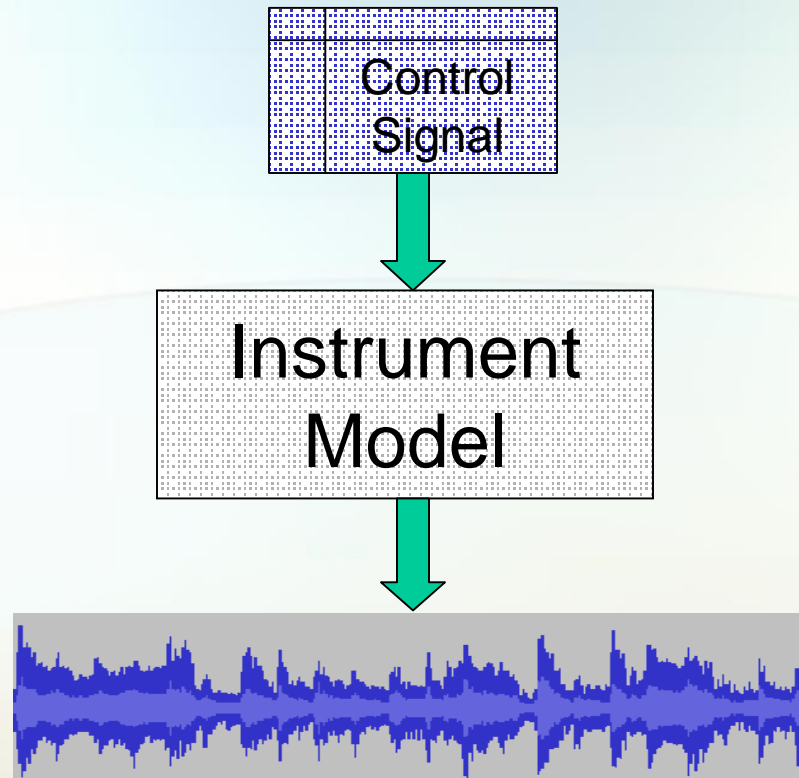
- Segmentation problem → Classification problem
- Hierarchical machine-learning framework
- Detect soft onset: compare frames separated by increasingly longer distances



# Roadmap

- ✓ Introduction
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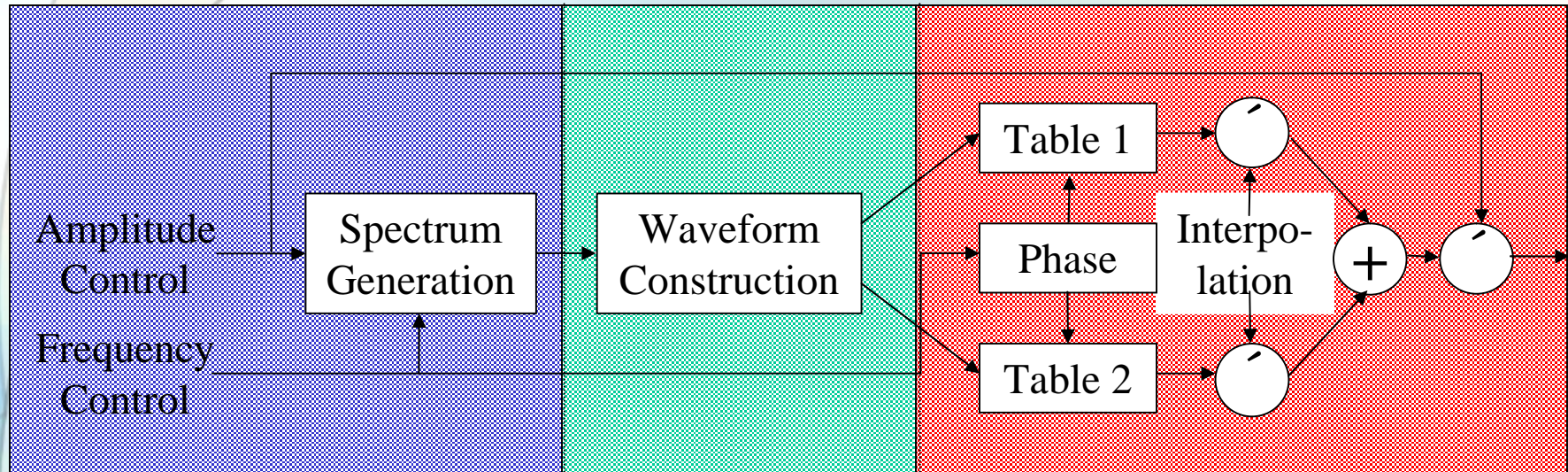
# Instrument Model



- **Harmonic Model + Residual model**



# Harmonic Model



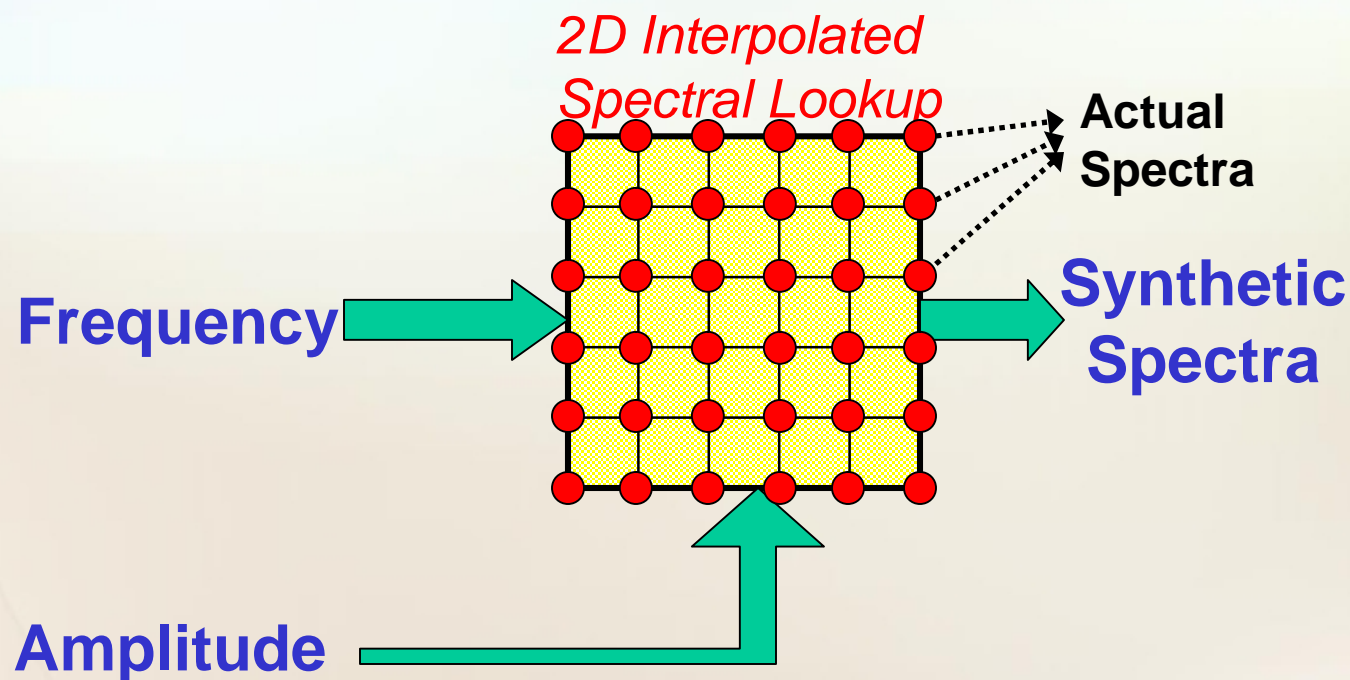
- **Control signals**  $\rightarrow$  **Spectra**
- **Spectra**  $\rightarrow$  **Wavetables**
- **Wavetables**  $\rightarrow$  **Sound samples**

# Control Signals Spectra

- **Spectral interpolation** (Dannenberg, et. al., 1998)
- **Memory-based approach** (Wessel, et. al., 1998)
- **Neural network** (Wessel, et. al., 1998)

# Spectral interpolation (Dannenberg, et. al., 1998)

- **Generate Spectral lookup table**
  - Record a set of sounds
  - Obtain a spectrogram for each sound
  - Retain specific spectra at thresholds

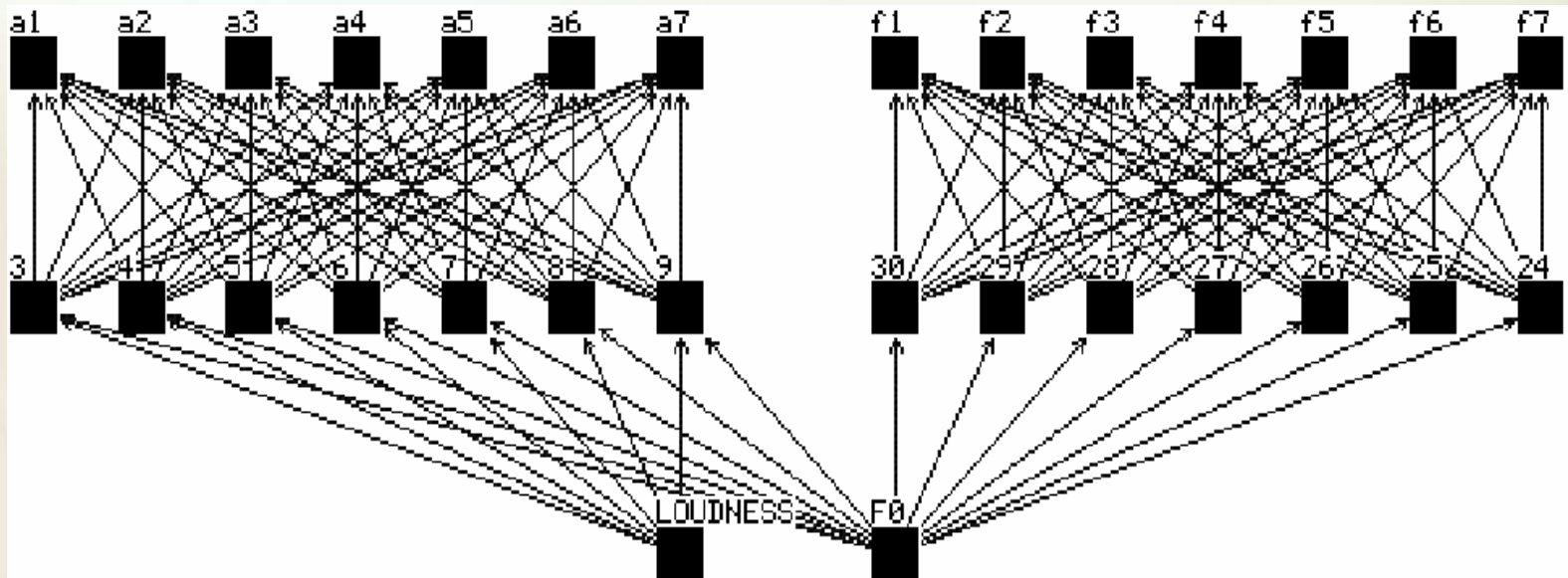


# Memory-based approach (Wessel, et. al., 1998)

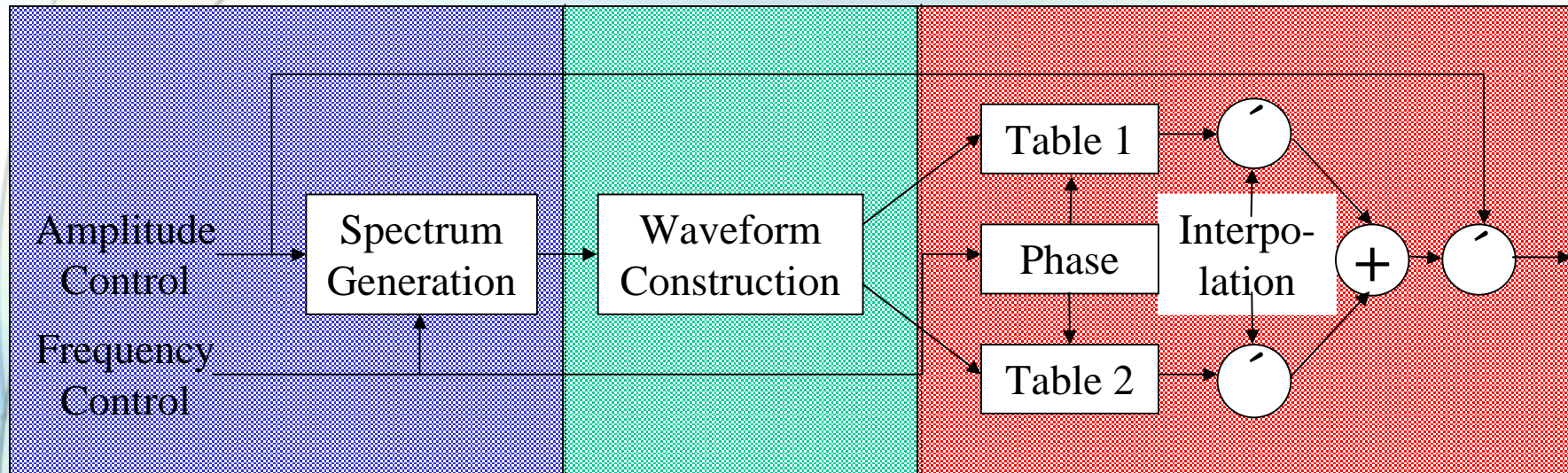
- **Index spectra in a  $n$  dim. space**
- **Interpolate among  $k$  nearest neighbors**
- **Special case**
  - **Spectral interpolation technique**
    - $n=2$  (frequency & amplitude)
    - $k=4$
    - **Linear interpolation**

# Neural network (Wessel, et. al., 1998)

- **A feed-forward neural network with multiples layers**
- **Input: frequency, amplitude**
- **Output: info of sinusoidal components**
- **Back-propagation learning method**
- **Advantage: very compact & generalize well**



# Harmonic Model







- **Control signals**  $\rightarrow$  **Spectra**
- **Spectra**  $\rightarrow$  **Wavetables**
- **Wavetables**  $\rightarrow$  **Sound samples**

# Residual Model

- **Modeling attacks**
  - Use recorded attacks
  - Phase matching
- **For other instruments**

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# Performance Model



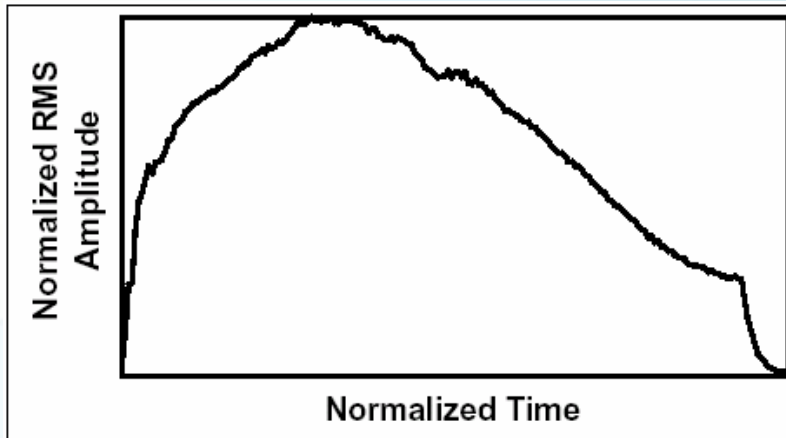
Performance  
Model



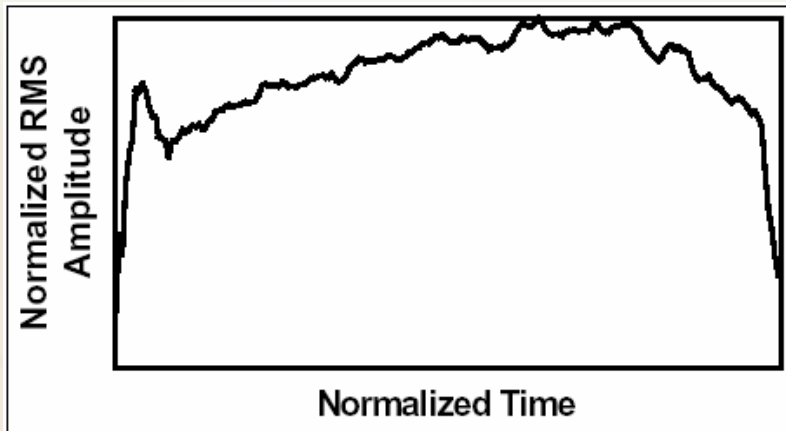
Control  
Signal

- **Control signals**
  - **Amplitude envelope**
  - **Frequency envelope**
- **Error metrics**
- **Envelope representation**
- **Mapping scheme**

# Amplitude Envelope



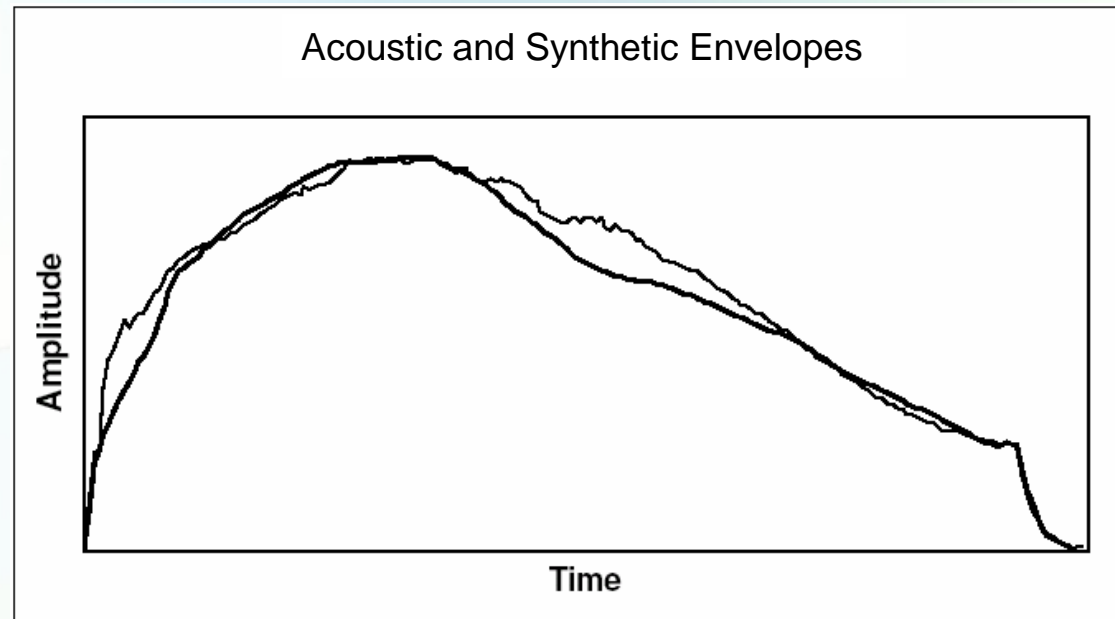
- **A tongued note**



- **A slurred note**

\*Figures borrowed from  
(Dannenberg, et. al., 1998)

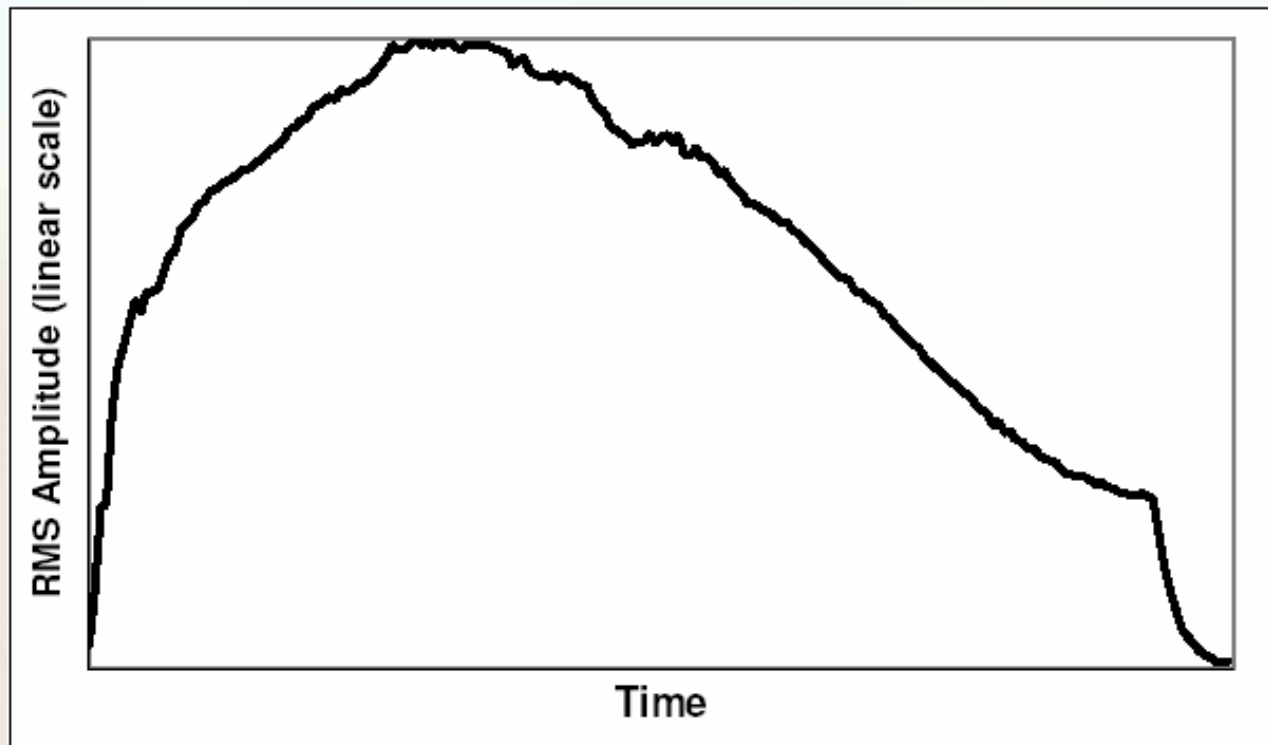
# Error Metrics



- **Typical metric: RMS error**
- **Recent work by (Horner et. al., 2004)**
  - **Measure perceptual difference**
  - **Useful reference for error metrics**

# Envelope Representation

- **Envelope representation**
  - **Characteristics of amplitude envelope**
    - Specific duration
    - Specific shape
    - Specific properties of each part








# Ways to Represent Envelopes

- **Collection of general parameters**
  - **Candidates: center of mass, global/local maximum/minimum, etc.**
  - **Manual vs. automatic selection**
- **Wavelets**
  - **Hierarchical decomposing functions**
  - **Very powerful and popular**

# Mapping Scheme

- **Non-linear regression**
  - Find music context  $\longleftrightarrow$  actual envelopes
  - **Examples:**
    - Neural network
    - Kalman filters  $X_k = AX_{k-1} + W_{k-1}$
    - Function approximation
- **Pattern clustering**
  - Classify envelopes into clusters
  - For each input data point:
    - Use corresponding representative envelope
    - Stretch, scale & interpolate accordingly
  - Considered as a form of case-based reasoning

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# Schedule (1)

<b>Oct 2004 ~ Nov 2004 (past) Thesis Proposal</b>	<ul style="list-style-type: none"><li>•Collect performance examples for initial experiments</li><li>•Get familiar with SNDAN package</li><li>•Read the original code by Dannenberg &amp; Derenyi</li><li>•Propose thesis topic</li></ul>
<b>Dec 2004 ~ May 2005      System Development</b>	
<b>Dec 2004 ~ Jan 2005</b>	<b>Implement Audio Alignment &amp; Segmentation module</b>
<b>Jan 2005</b>	<b>Incorporate SNDAN package to training data pre-processing stage</b>
<b>Feb 2005</b>	<b>Develop and compare instrument models</b>
<b>Mar 2005 ~ Apr 2005</b>	<b>Design and implement performance model</b>
<b>May 2005</b>	<b>System integration and testing</b>



# Schedule (2)

<b>Jun ~ Aug 2005</b>		<b>System Evaluation &amp; Tuning</b>
<b>Jun 2005</b>	<b>Model other instruments</b>	
<b>Jul 2005</b>	<b>Synthesize other types of music</b>	
<b>Aug 2005</b>	<b>System and model evaluation and fine tuning</b>	
<b>Sep ~ Nov 2005</b>		<b>Writing Thesis</b>
<b>Sep 2005 ~ Nov 2005</b>	<b>Thesis write-up and revisions</b>	
<b>Nov 2005</b>	<b>Thesis defense</b>	

# Conclusion

- **Propose a scheme:**
  - **automatically construct**
  - **high-quality instrument synthesis**
  - **by learning from performance examples**
- **Machine learning → a crucial role.**
- **Future work**
  - **Modeling different instruments**
  - **Modeling different music styles**
  - **Make it work in real-time**

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# Thank You

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- **Contact**  
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