Hybrid Speech Synthesis

Simon King

Centre for Speech Technology Research

University of Edinburgh

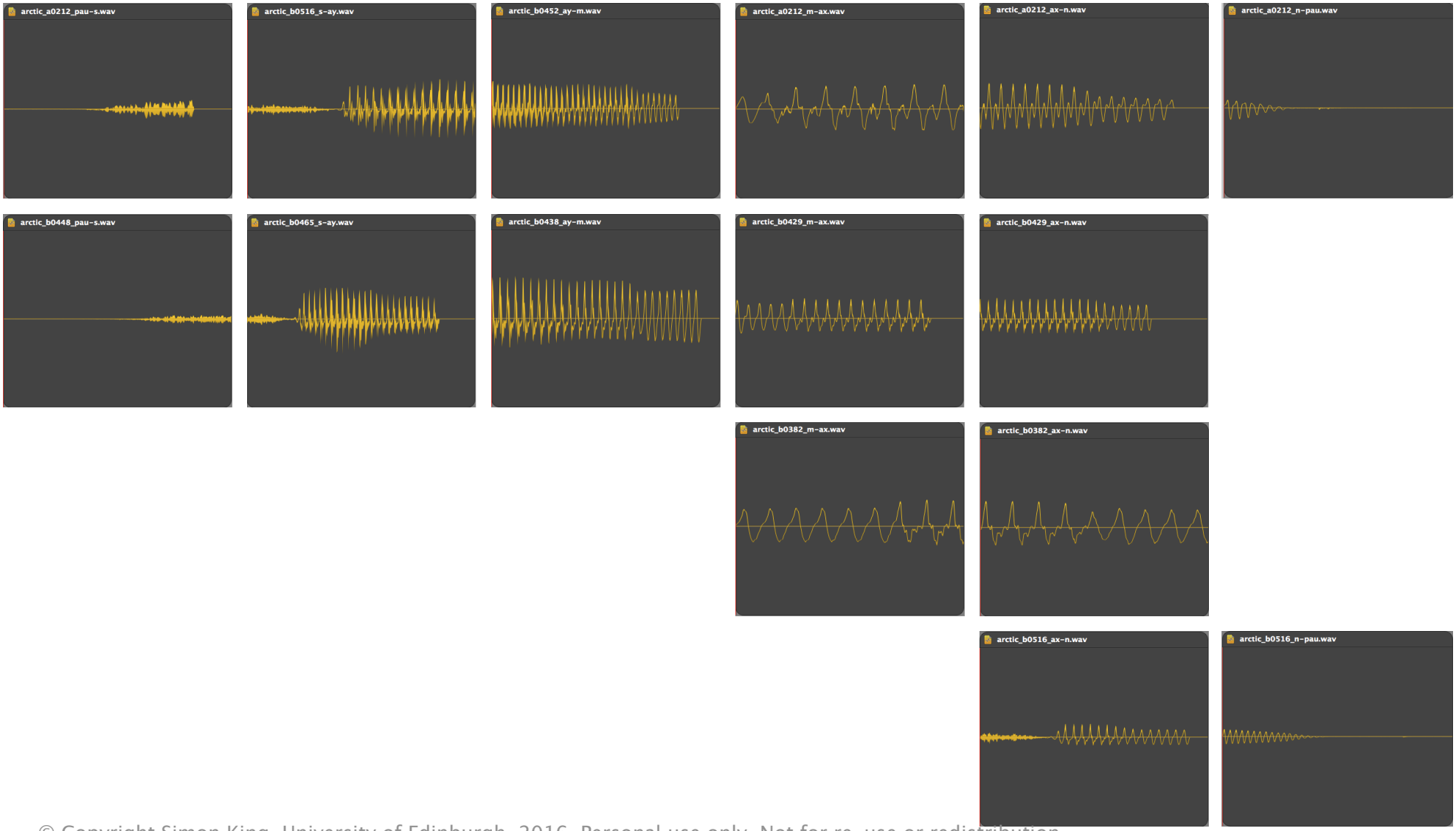
What are you going to learn?

- Another recap of unit selection
  - let's properly understand the "Acoustic Space Formulation" of the target cost
- Comparing IFF and ASF target cost functions
  - the case of prosody prediction
- Core idea of hybrid speech synthesis
- Case study: Microsoft's 'trajectory tiling' method

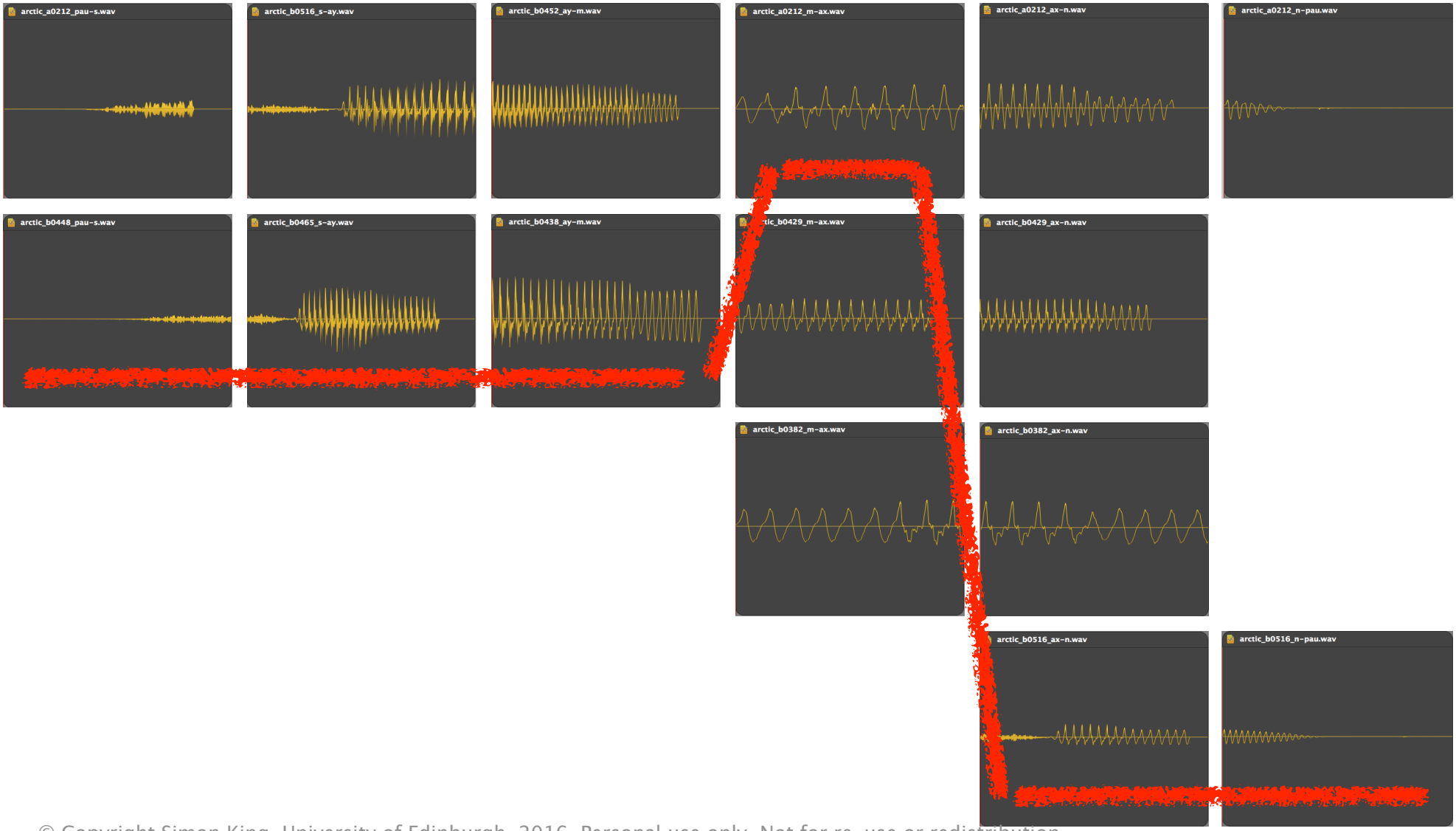
Hybrid Speech Synthesis

Recap of unit selection (yes, again!)

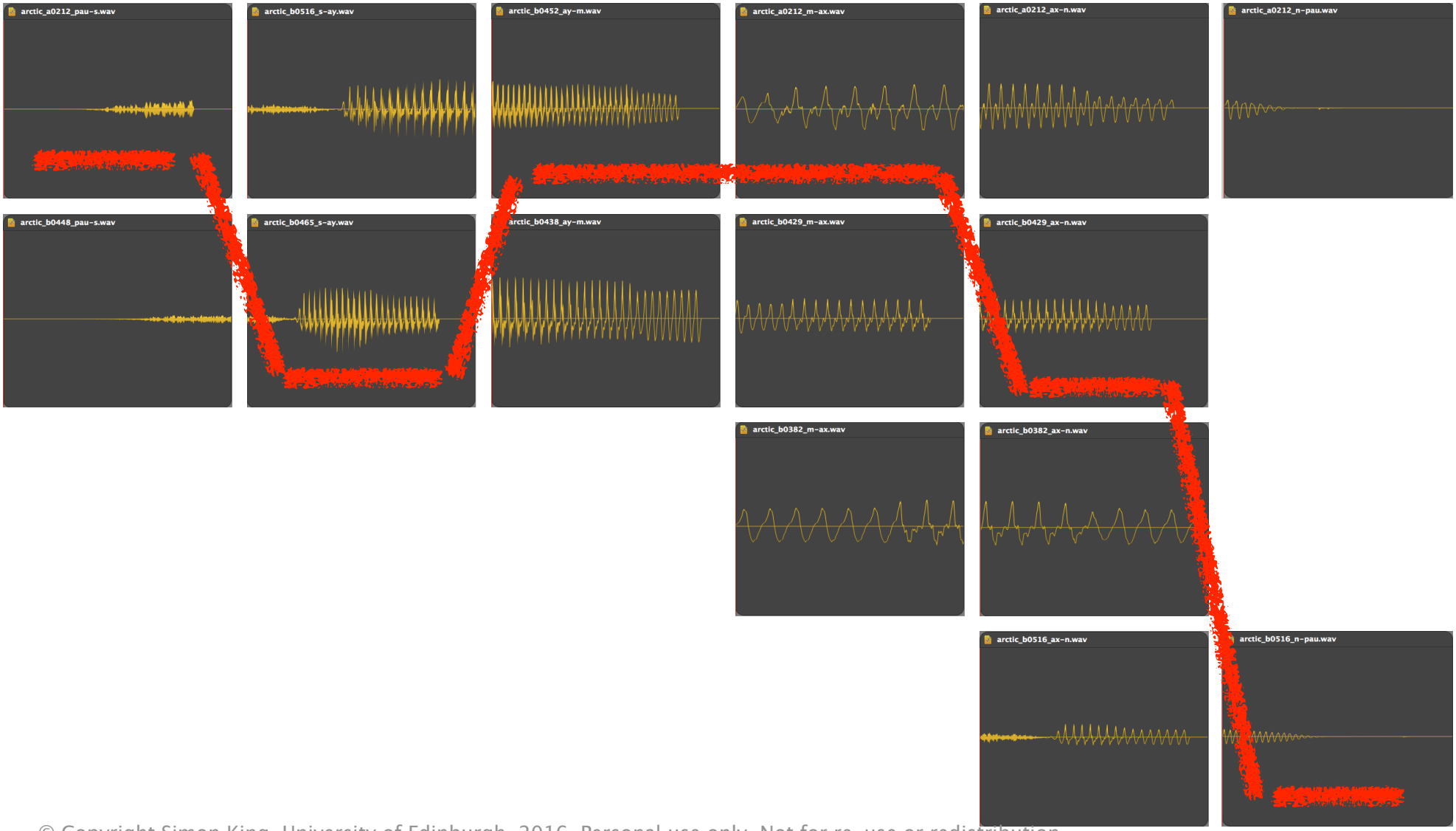
“Simon”



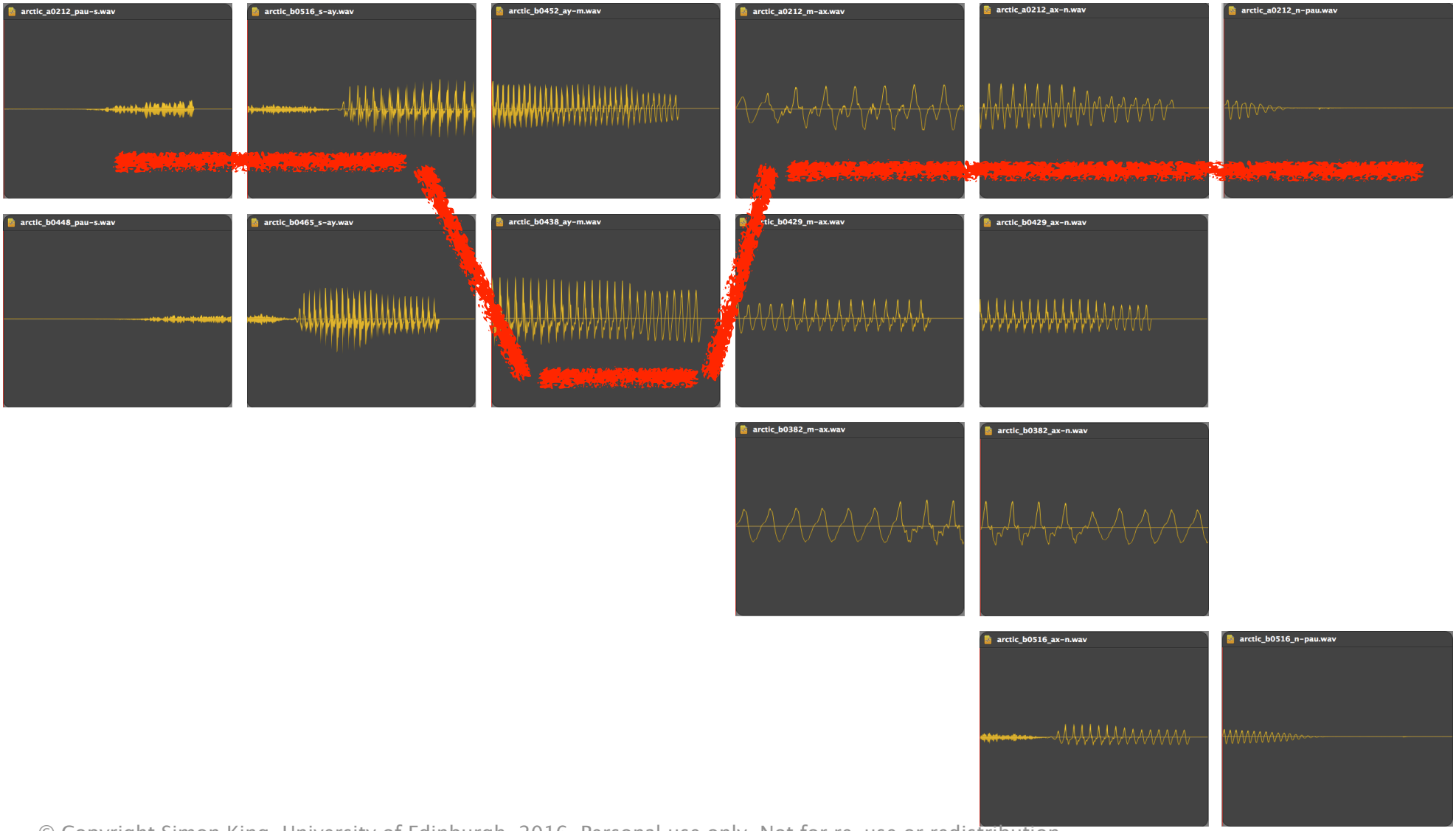
“Simon”



“Simon”



“Simon”



Possible formulations of the target cost

- The ‘distance’ between a candidate unit and the ideal (i.e., target) unit is measured by the **target function**

- Taylor describes two possible formulations of the target function
  - independent feature formulation (IFF) - this is what Festival’s Multisyn engine uses (*well, mostly*)
  - acoustic-space formulation (ASF) - **this is hybrid speech synthesis**

The acoustic-space target-function formulation (ASF)

- To use an ASF target cost, we need to do "***partial synthesis***"
  - i.e., we need to predict some acoustic properties
    - which properties?
    - how do we predict them?
    - how exactly do we then use them in an ASF target cost?

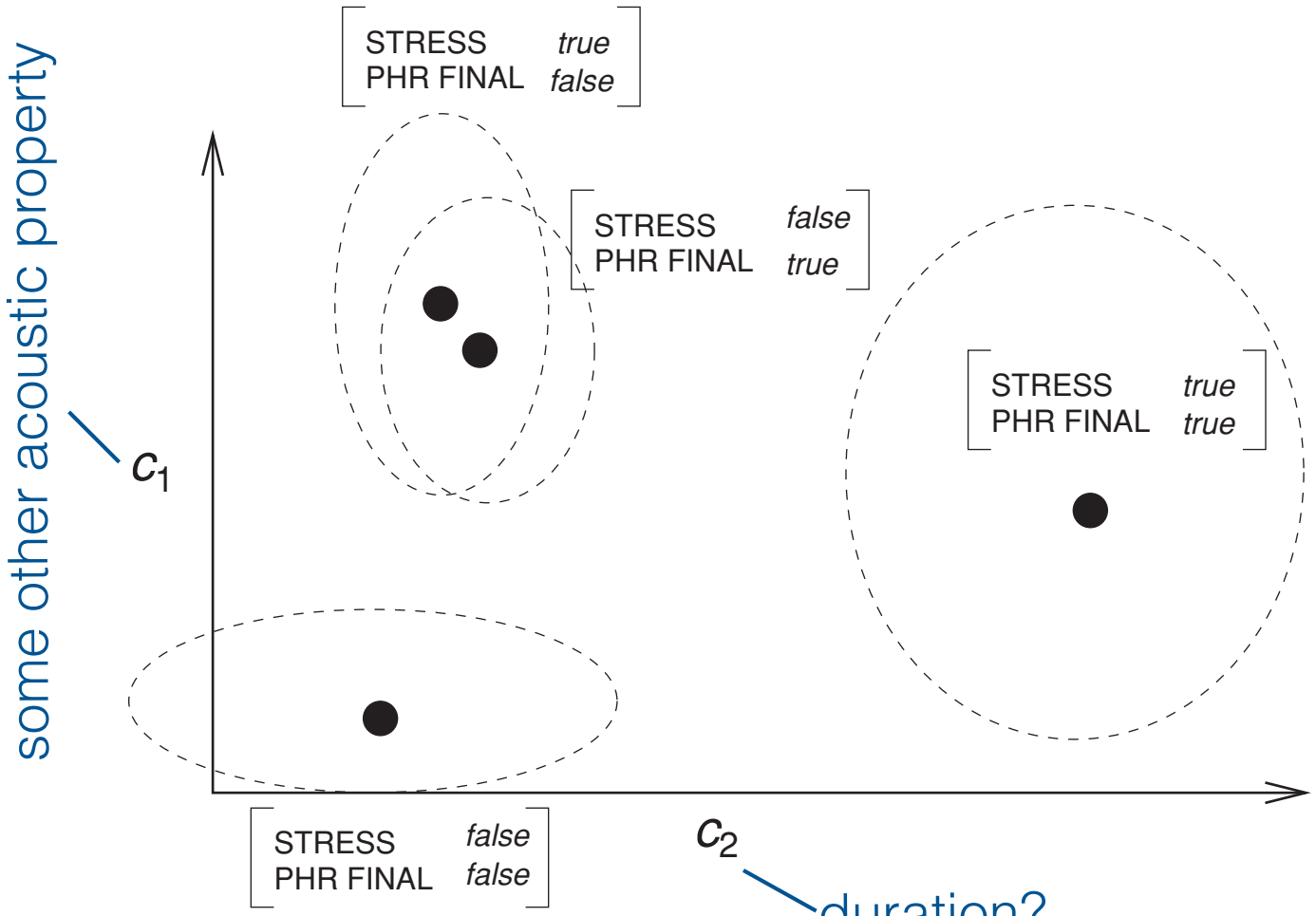
- Predicting acoustic properties
  - **classification and regression trees**, as we saw in Speech Processing
  - or any other predictive model you care to use

What acoustic properties to predict?

- We have choices:
  - a few simple acoustic properties such as F0 and duration
    - would probably combine with aspects of an IFF target cost function
  - a more detailed specification such as spectral shape (e.g., represented as cepstral coefficients)
    - possibly a full set of vocoder features (as per HMM or DNN synthesis)

The acoustic-space target-function formulation (ASF)

- Visualising the acoustic space (Taylor, figure 16.6)



Hybrid IFF + ASF target cost

- Real systems often actually uses a hybrid IFF + ASF target cost function
  - it's easy enough in principle to combine them: some sub-costs use linguistic features, others use acoustic features

- Why?
  - partial synthesis is a way to escape some of the sparsity problems of linguistic features: many different feature combinations lead to the same acoustic property value (e.g., F0)
  - but our small set of acoustic properties (F0, duration, ..?) doesn't capture all possible acoustic variation
    - e.g., voice quality, such as phrase-final creaky voice

Hybrid Speech Synthesis

Understanding the difference between IFF and ASF
- the case of prosody prediction

Prosody generation in unit selection: IFF approach

- the key question is: ***what linguistic features*** should the target cost compare?

- well - they can be anything we can reliably predict from the text

- should that include **ToBI accents & boundary** tones, for example?
  - how would we predict these?
    - choose your classifier: ……
    - list available predictors: ……
    - obtain training data: ……
  - how accurate would those predictions be?

Prosody generation in unit selection: ASF approach

- ***how to predict*** the acoustic features for the target?
  - assume we will use ToBI as the symbolic representation of prosody
  - step 1: predict ToBI symbols from text
    - a classification task, as in the IFF approach
  - step 2: render ToBI symbols as an F0 contour
    - a regression task - will need training on data

- ***how to compare*** the acoustic features between target and candidate?
  - Euclidean distance between F0 contours?
  - is that perceptually relevant?

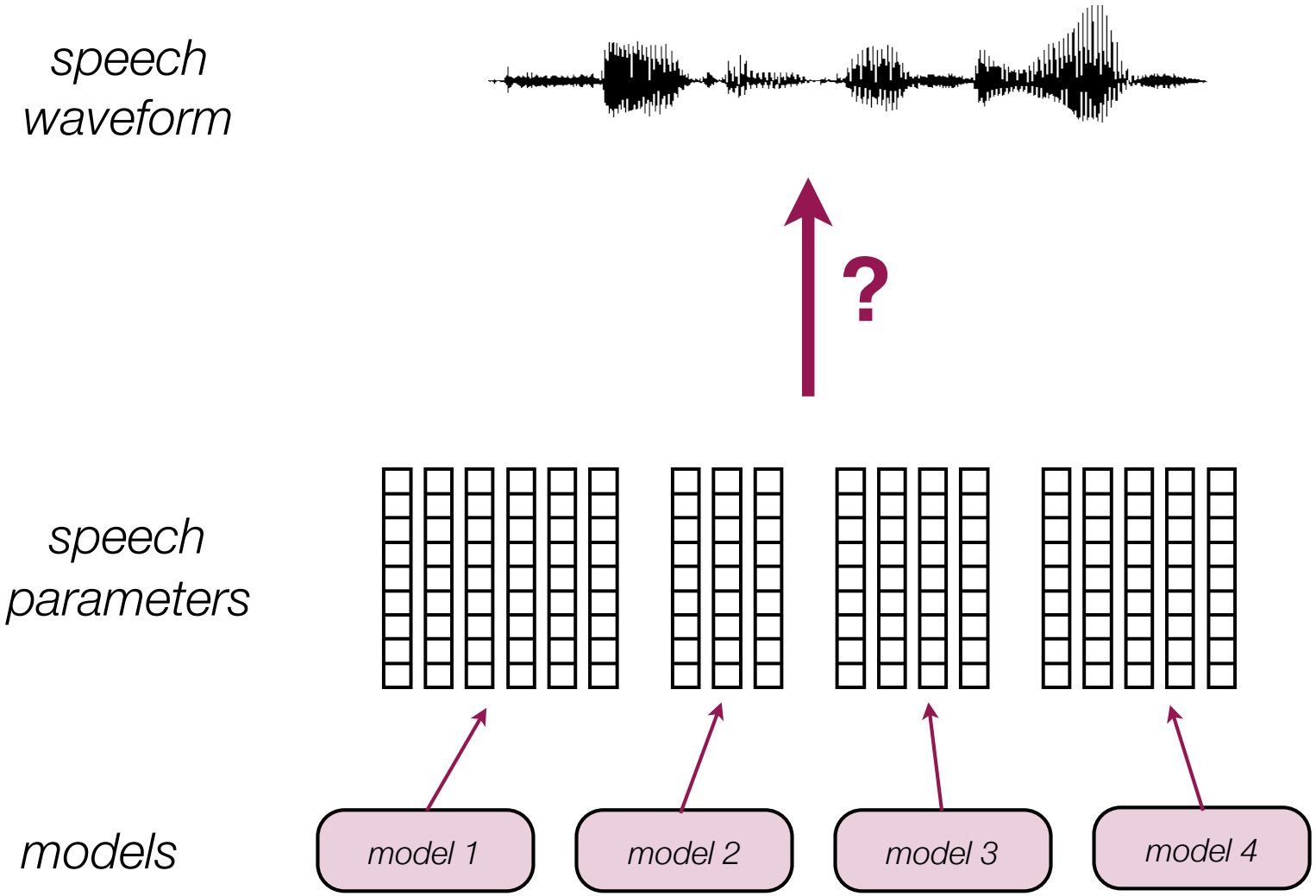
Hybrid Speech Synthesis

The core idea

Hybrid approaches

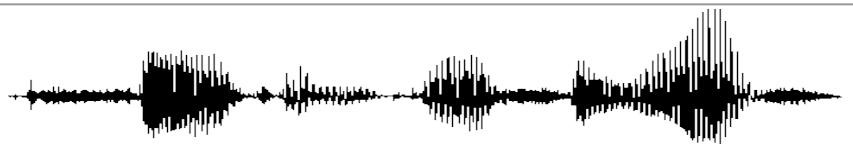
- HMM or DNN synthesis
  - flexible, somewhat robust to labelling errors
  - but limited in naturalness by the vocoder (amongst other things)
- Unit selection
  - potentially excellent naturalness (due to **waveform** concatenation)
  - but IFF target cost is hand-crafted; join cost rather naive
    - fragile - e.g., easily affected by labelling errors
    - hard to optimise for each new speech database
- Hybrid synthesis
  - robustness and learning-from-data
  - waveform concatenation

Hybrid speech synthesis

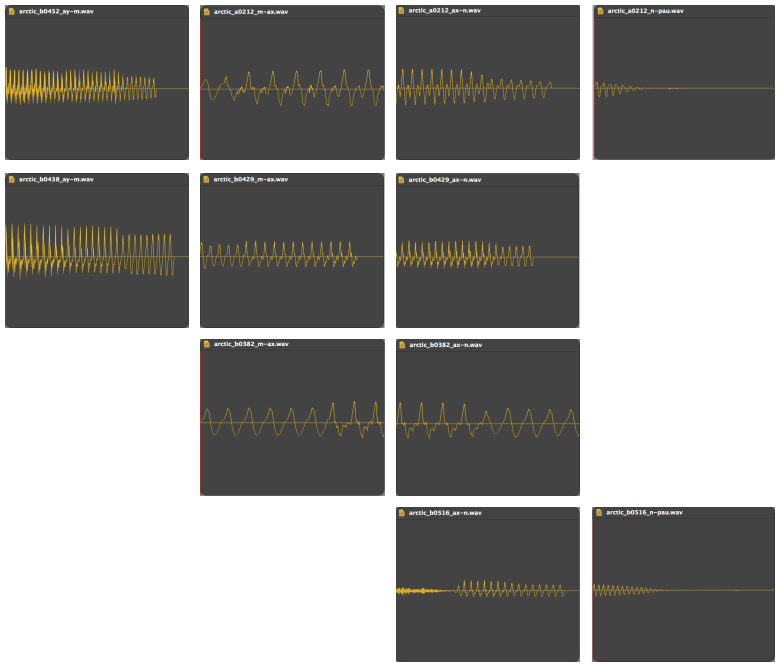


Hybrid speech synthesis

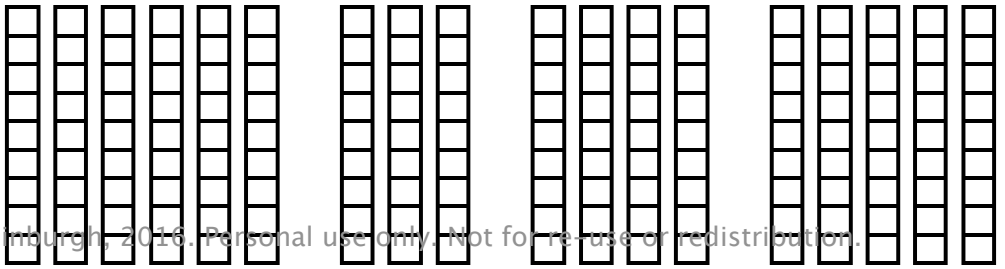
speech waveform



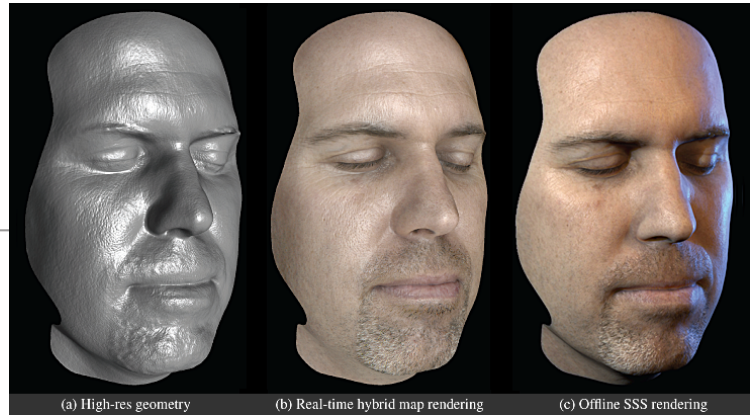
unit inventory

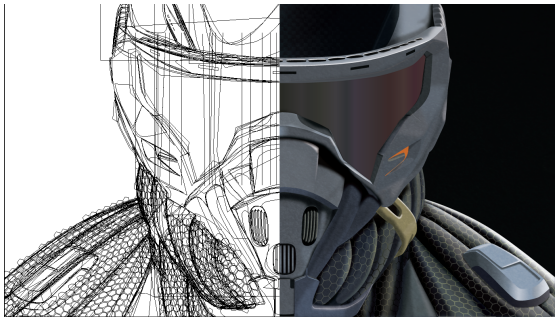


speech parameters



Various forms of hybrid synthesis





- Trajectory tiling (Microsoft Research)
  - generate speech parameters from HMM
  - select closest matching waveform units
    - can formulate this probabilistically
    - effectively, HMMs are the target cost
  - perform unit selection search procedure
  - **concatenate waveforms**
- Multiform synthesis (Nuance, used in main product)
  - concatenate an **alternating** sequence of
    - waveform units
    - speech generated from HMMs + vocoder
  - perceptual considerations: use HMMs when listener will not hear the difference

Hybrid Speech Synthesis

Hybrid speech synthesis: the “trajectory tiling” approach

This content is based on the paper:

Y. Qian, F. K. Soong and Z. J. Yan “A Unified Trajectory Tiling Approach to High Quality Speech Rendering” *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

and the following slides contain some figures taken from that paper.

Trajectory tiling

- Core idea
  - **generate** speech parameters using a statistical model
    - spectral envelope
    - F0
    - energy (gain)
  - find a sequence of waveform fragments that **matches** these parameters
  - **concatenate** that sequence

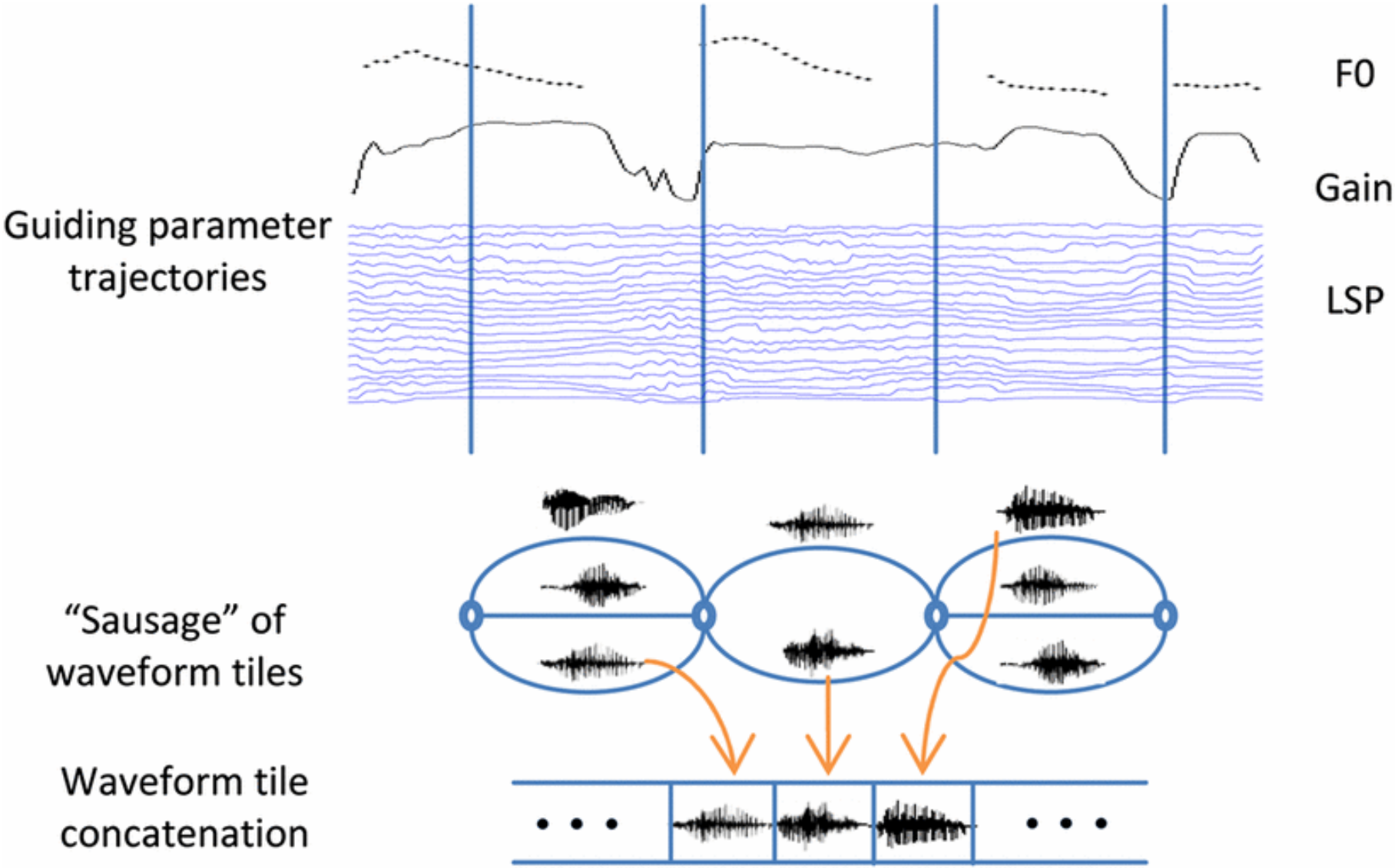


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Measuring the distance between waveform fragments and the trajectories from the HMM

- How might we do this?
  - extract from the waveforms
    - spectral envelope
    - energy
    - F0
  - **target cost** = Euclidean distance (between the above features, summed over all frames of a unit)
  - **join cost** = Euclidean distance between the above features across a concatenation point

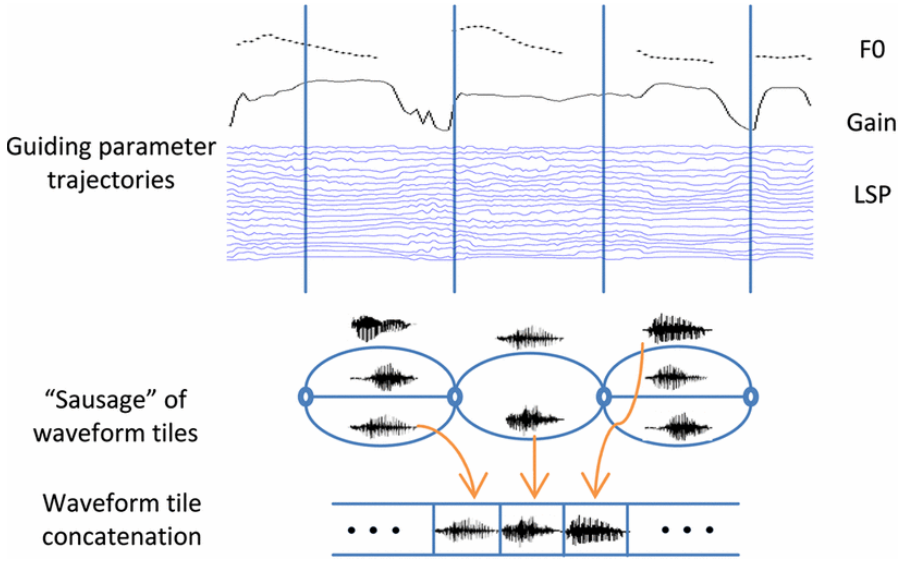


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Measuring the distance between waveform fragments and the trajectories from the HMM

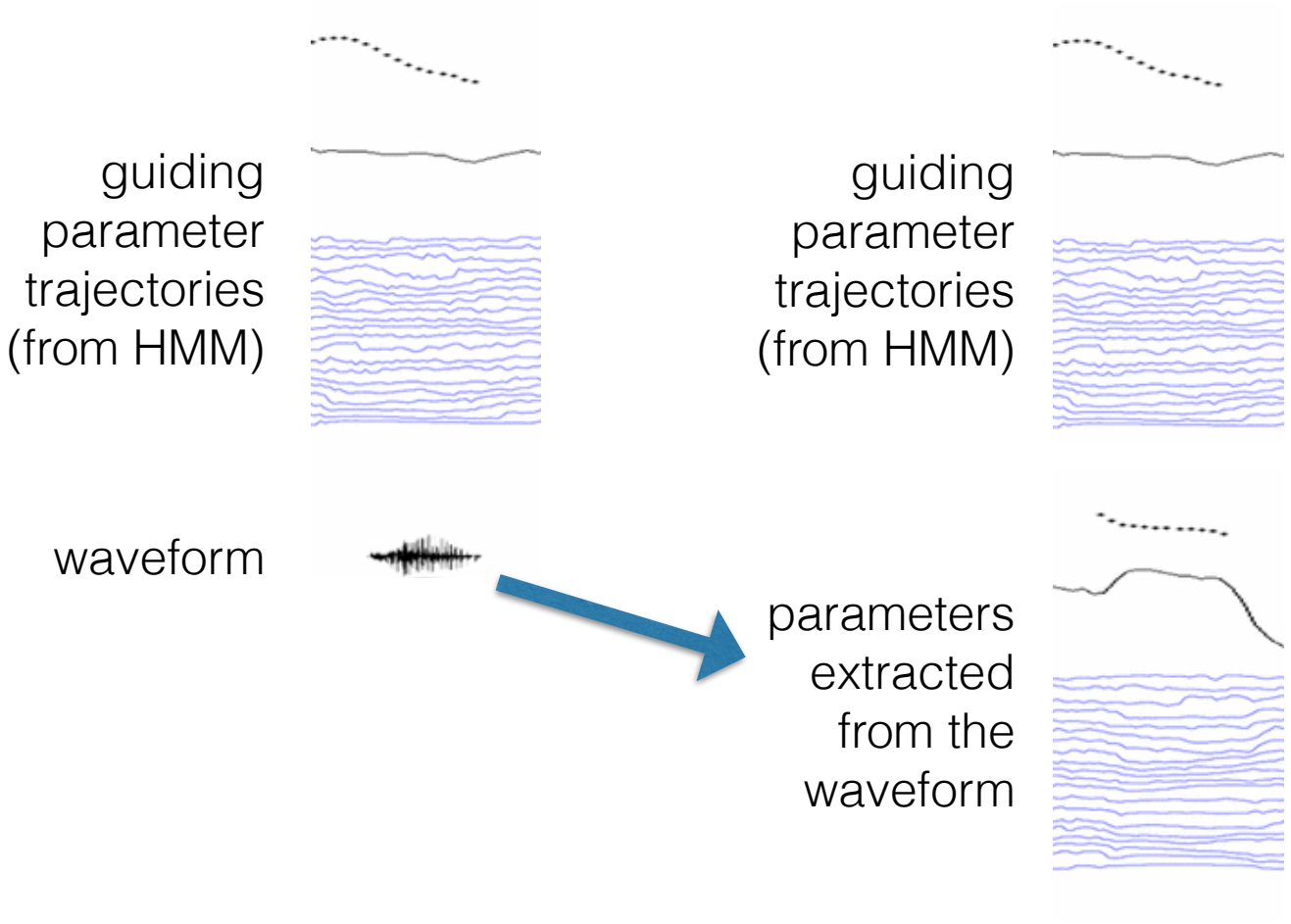


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Using linear prediction features (source-filter model)

- extract from the waveforms
  - line spectral pairs (**LSPs**)
  - gain (of the LPC filter)
  - F0
- **target cost** = Euclidean distance (between the above features, summed over all frames of a unit)

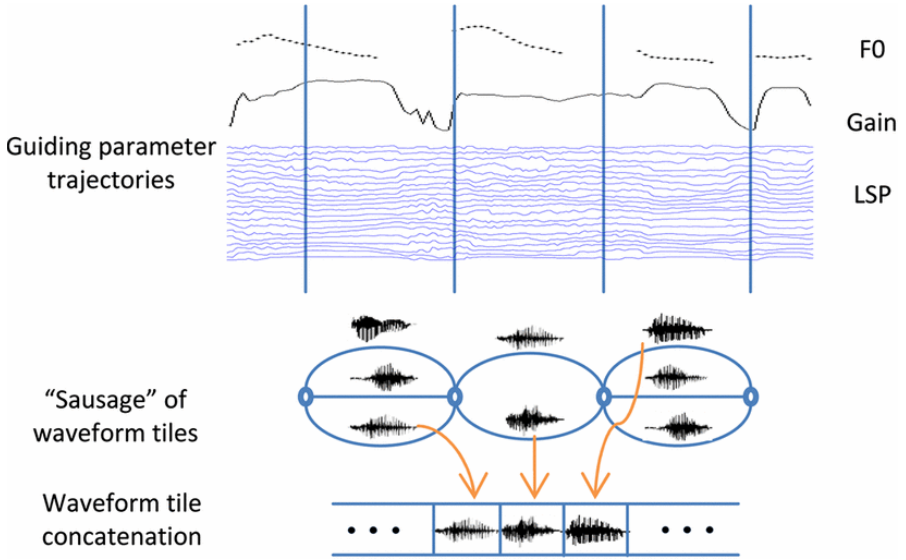


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Mismatch between natural parameter trajectories and those generated by HMMs

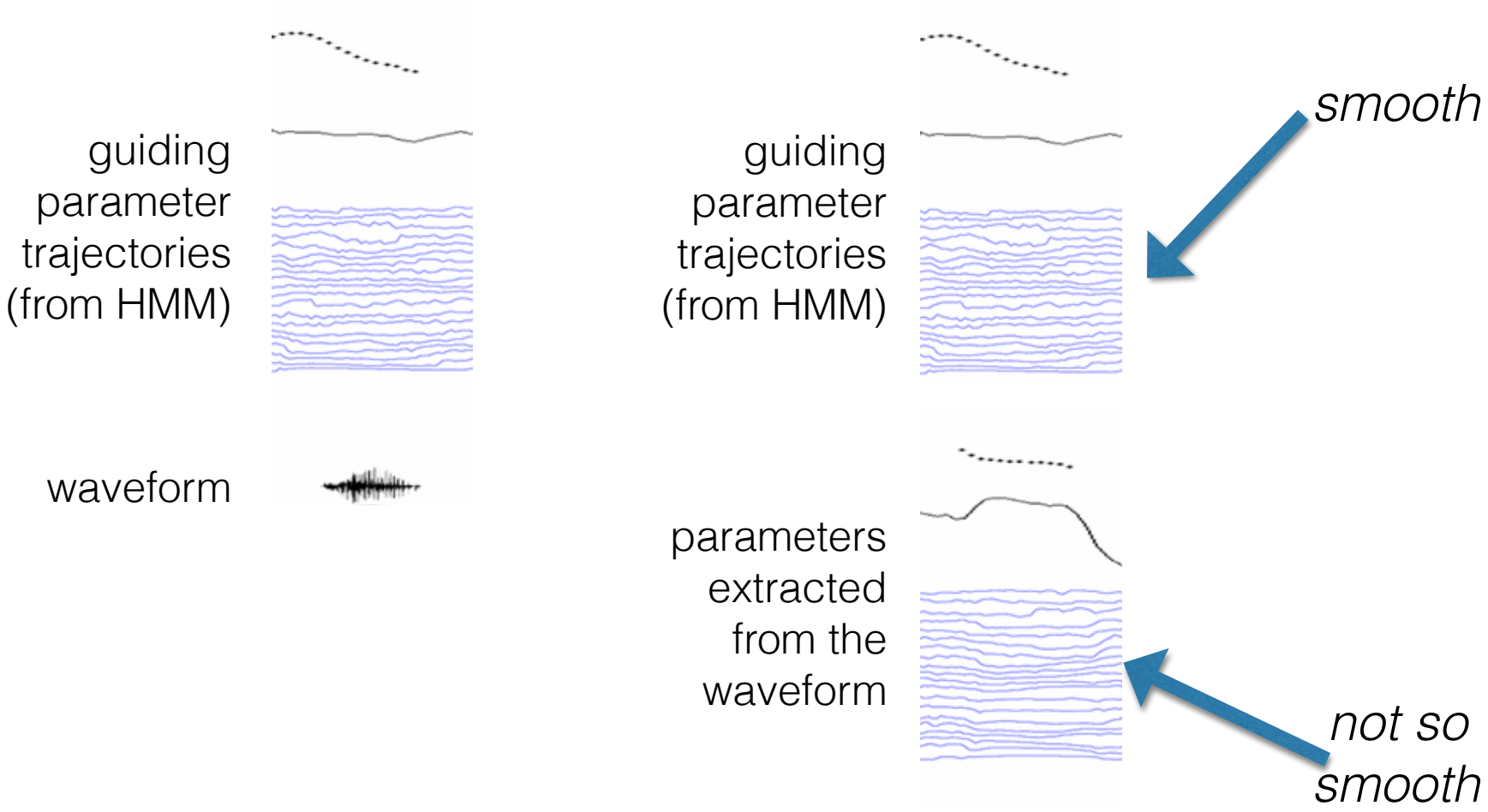
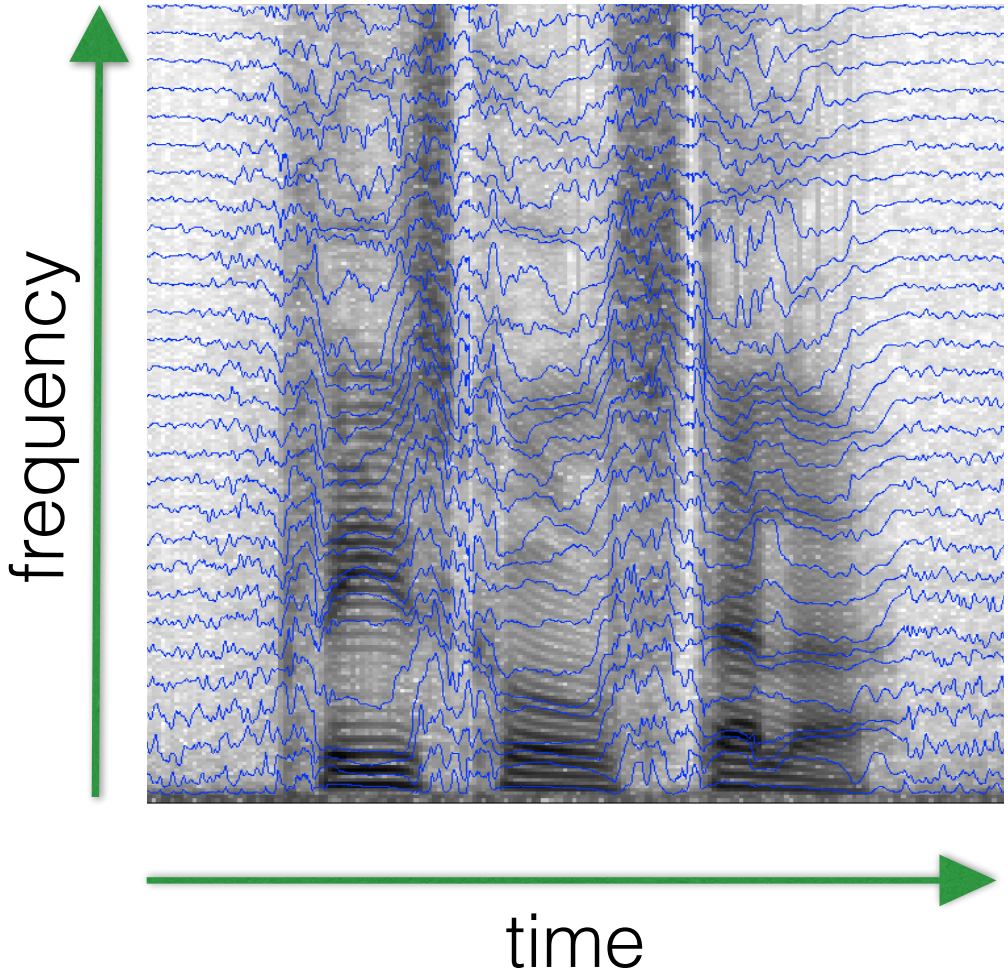
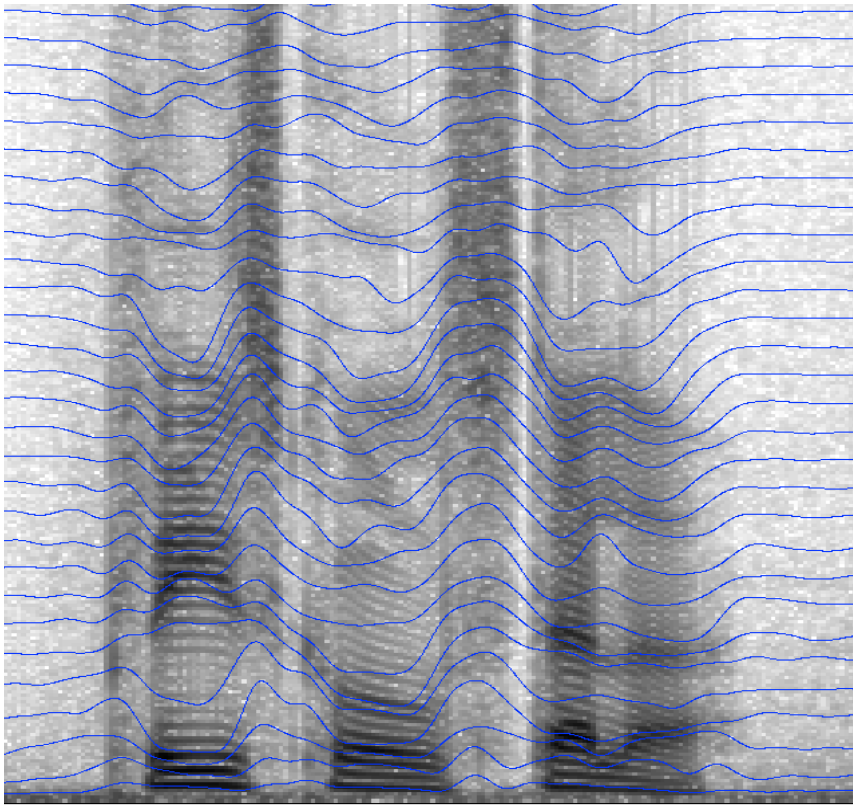


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

LSPs: extracted from waveform vs. generated by HMM





Reduce mismatch between natural parameter trajectories and those generated by HMMs

- instead of extracting these features from the waveforms
  - line spectral pairs (LSPs)
  - gain (of the LPC filter)
  - F0
- **generate them using HMMs**
  - train models on the full database of waveforms (training data)
  - synthesise parameter trajectories for this training data from these models

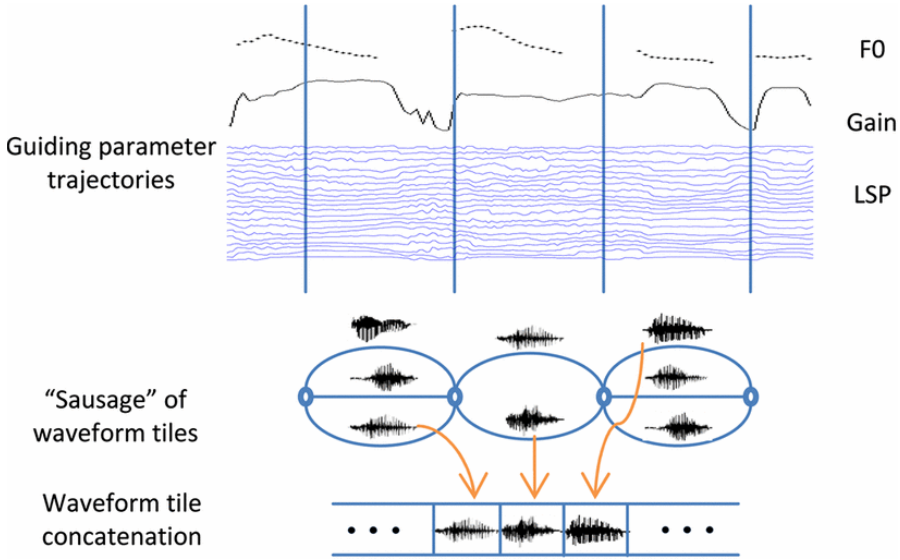


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

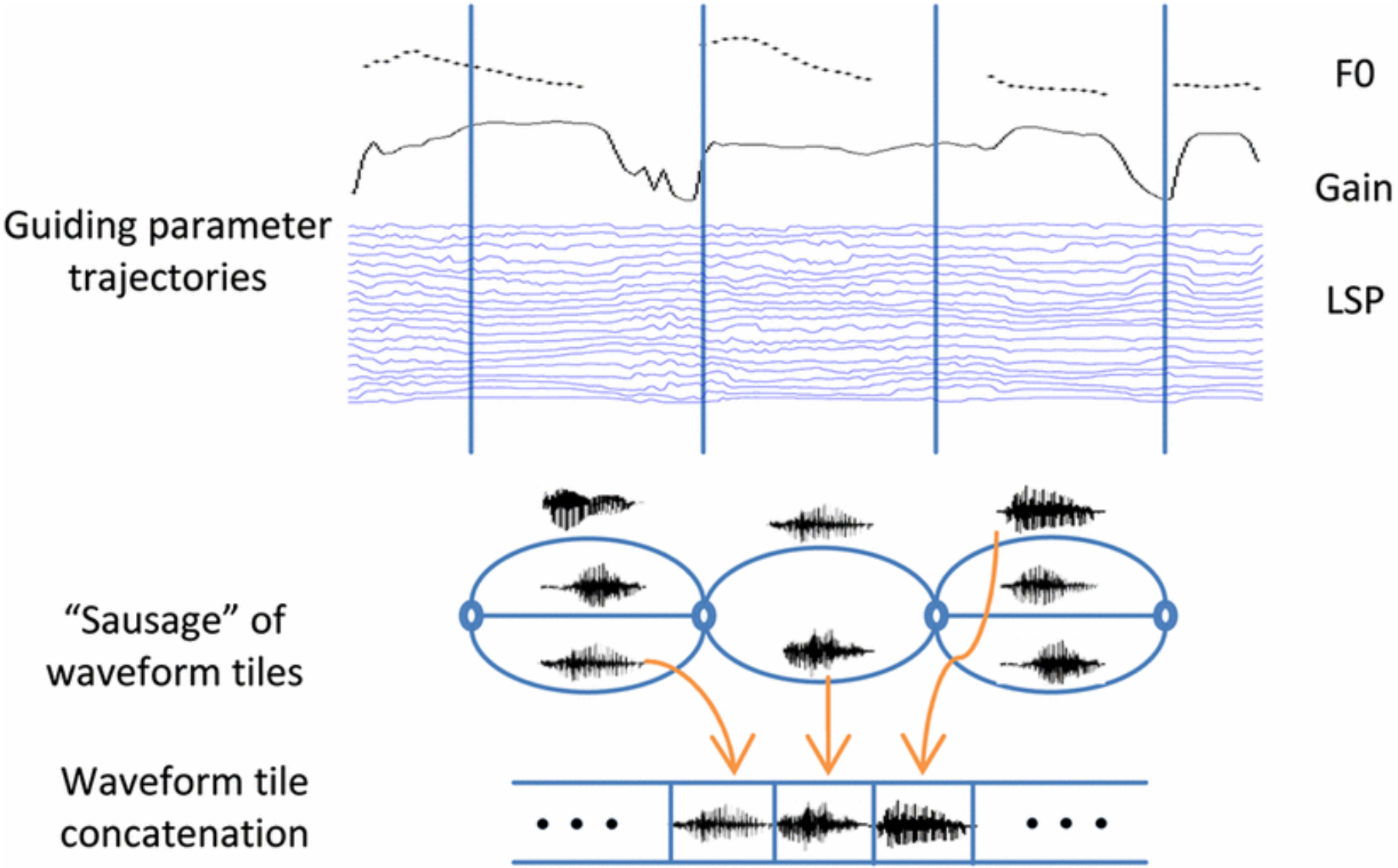


Figure 1 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

What is NCC (Normalised Cross Correlation)?

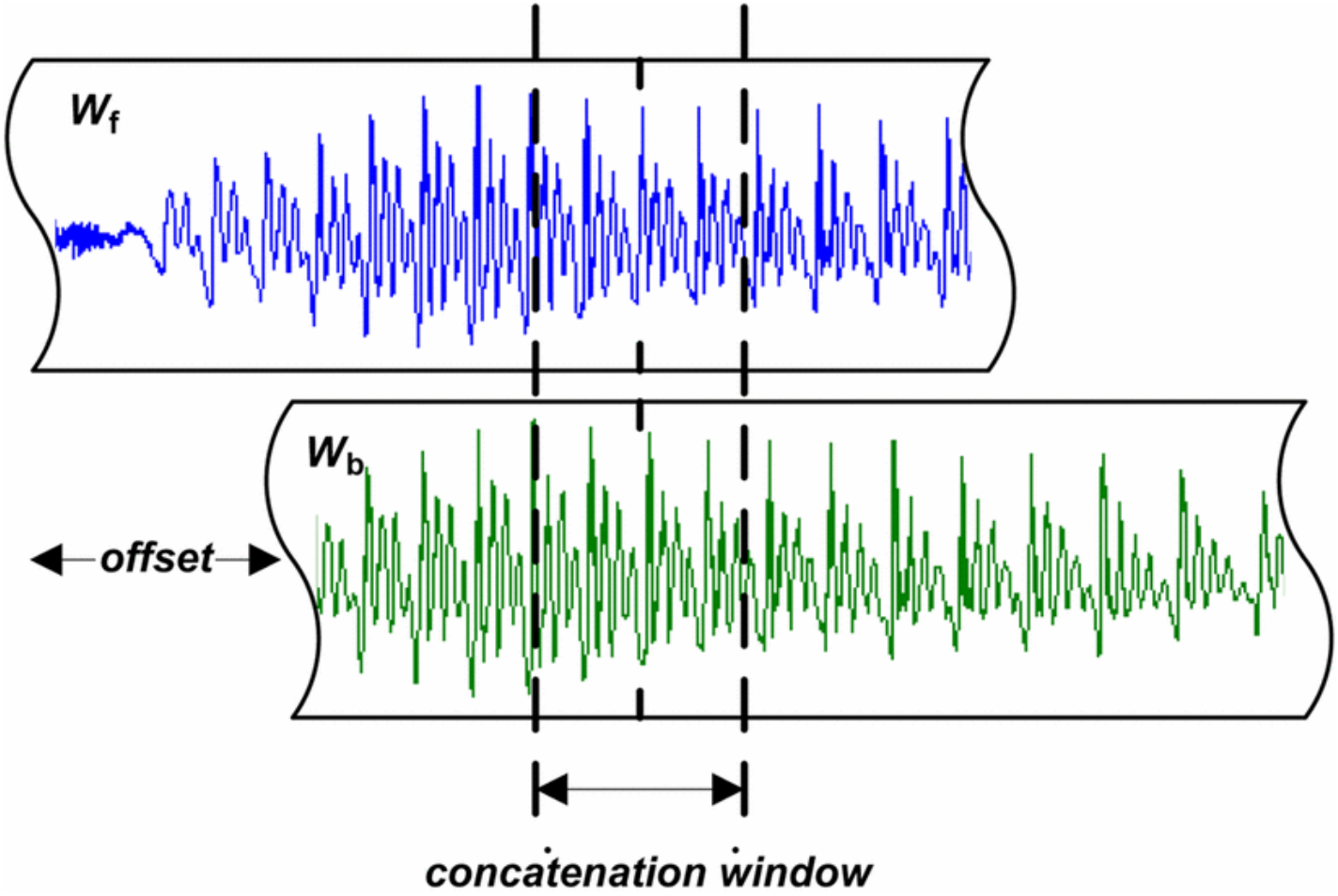


Figure 4 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Training the ‘guide’ HMM system

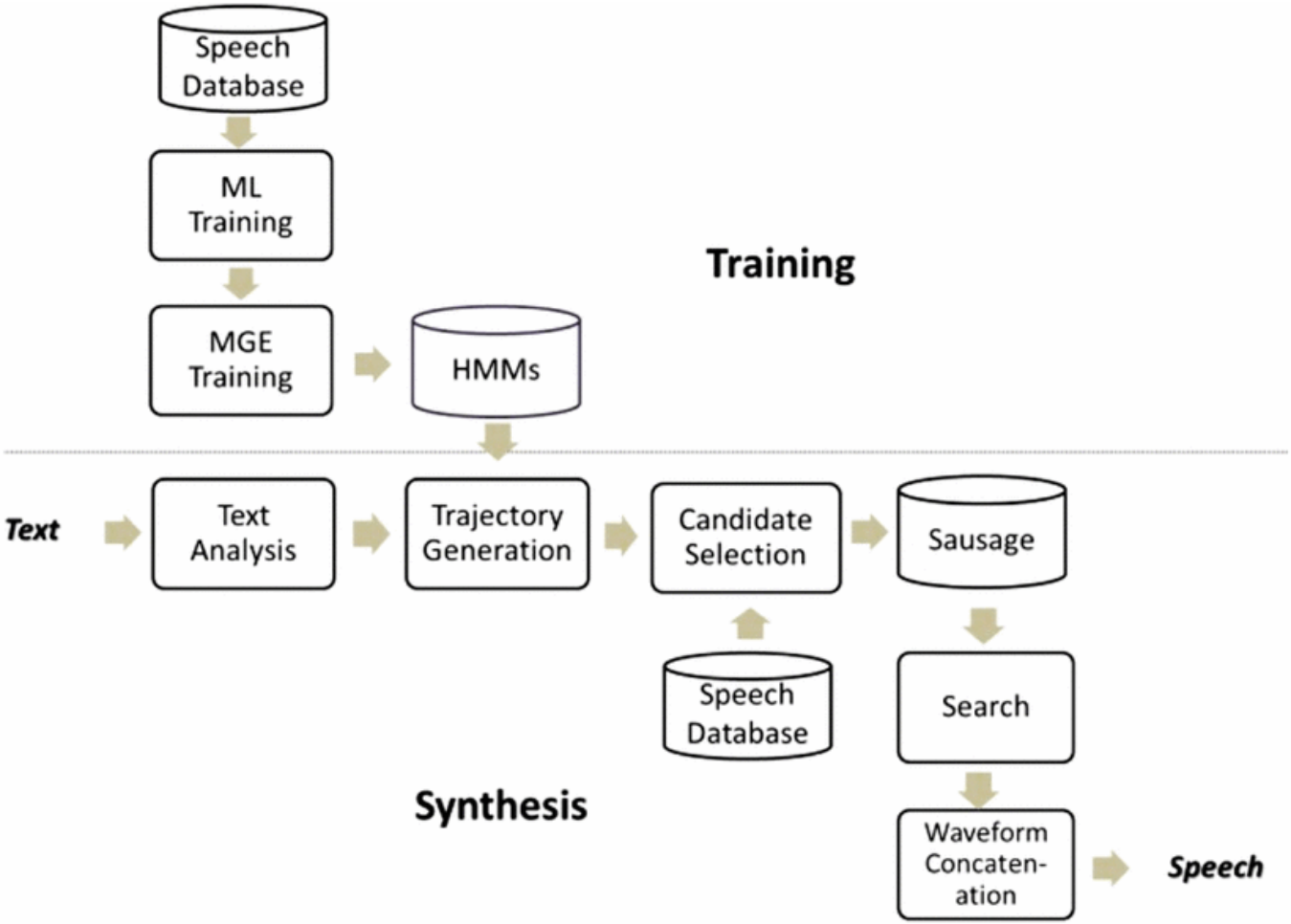


Figure 2 from Y. Qian, F. K. Soong and Z. J. Yan “A Unified Trajectory Tiling Approach to High Quality Speech Rendering” *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460

Trajectory tiling

- Core idea
  - **generate** speech parameters using a statistical model
    - spectral envelope
    - F0
    - energy (gain)
  - find a sequence of waveform fragments that **matches** these parameters
  - **concatenate** that sequence
- Additional details
  - use **LSFs** for spectral envelope
  - for the purposes of distance calculation, **replace** waveform fragments with parameters **generated by HMMS** (trained on that same data)
  - use a join cost that both
    - measures **mismatch**
    - finds good **concatenation points**

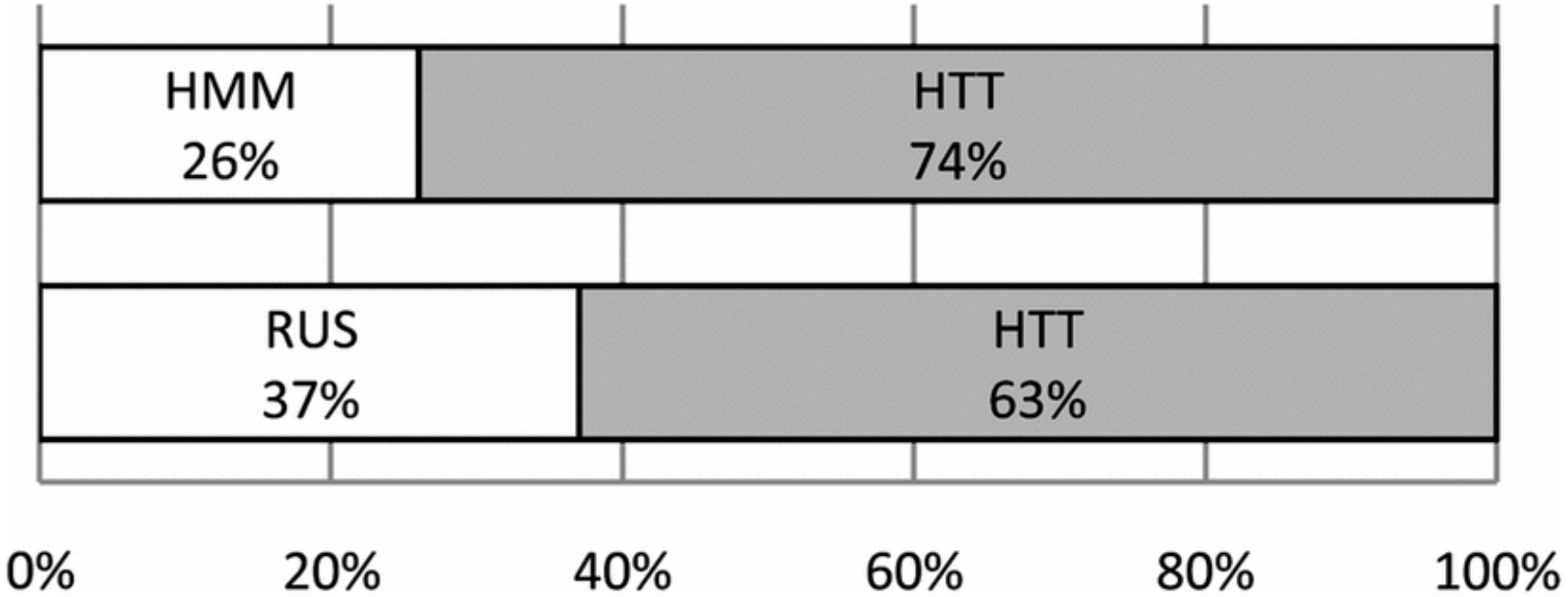


Figure 7 from Y. Qian, F. K. Soong and Z. J. Yan "A Unified Trajectory Tiling Approach to High Quality Speech Rendering" *IEEE Trans. Audio, Speech, and Language Proc.* 21 (2), pp. 280-290, 2013. DOI:10.1109/TASL.2012.2221460