



Footprint Reduction of Concatenative Text-To-Speech Synthesizers using Polynomial Temporal Decomposition

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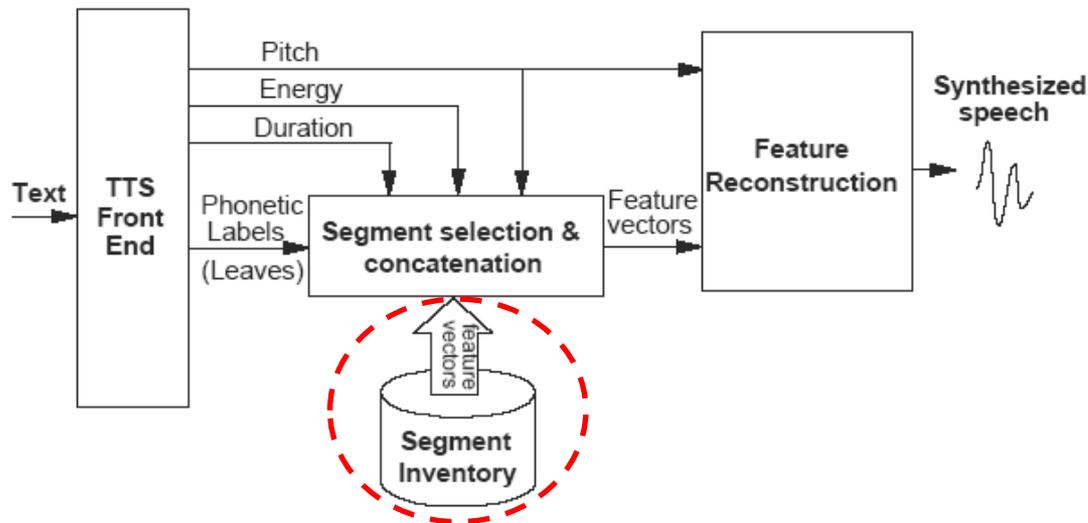
(*) Signal & Image Processing Lab - Technion

(#) IBM – Haifa Research Labs

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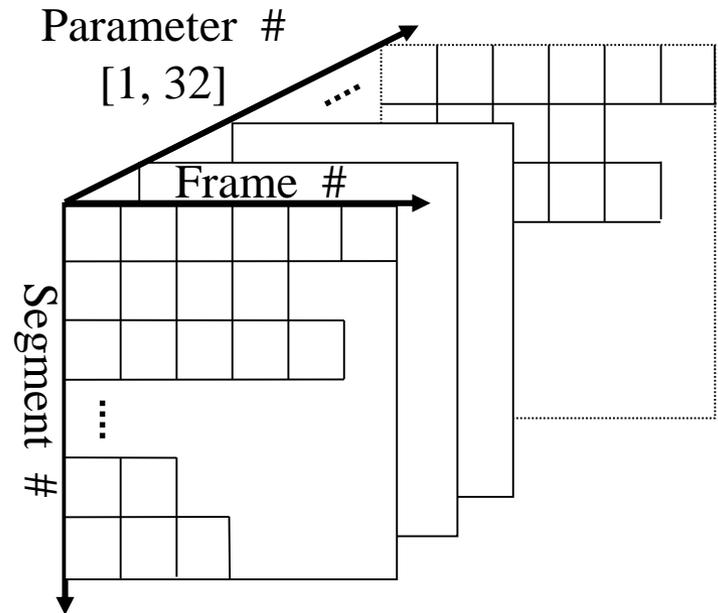
Introduction

- **Goal:** Further footprint reduction of a small footprint IBM Concatenative Text-To-Speech (CTTS) system.
- **Method:** Re-compression of the stored speech parameters in the speech segment database.
- **Proposed technique:** Remove redundancies between speech frames using Polynomial based Temporal Decomposition (TD).



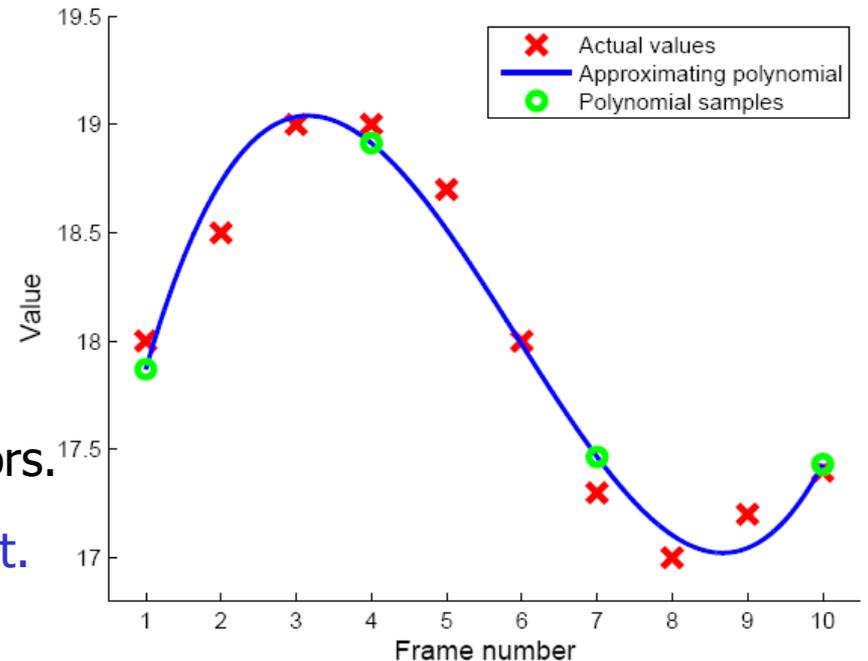
CTTS database structure

- The database consists of **acoustic leaves**, each corresponding to a specific **sub-phoneme** in a specific context.
- 5-10 **speech segments** are stored in each acoustic leaf.
- Each speech segment consists of one or more **speech frames**, each represented by a parametric spectral model, with 32 amplitude parameters per speech frame.



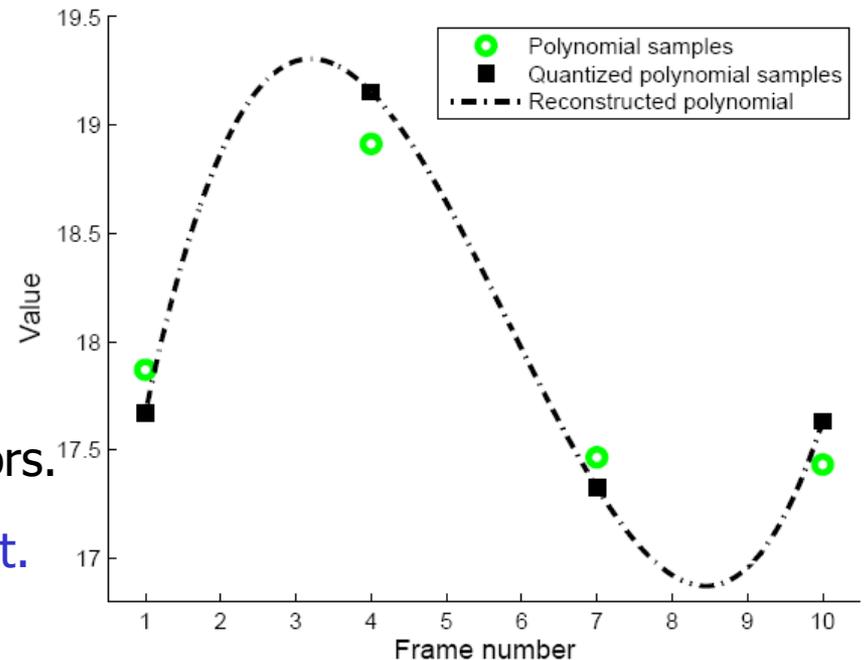
Polynomial TD

- Initially proposed by Dusan *et al.* (2007).
- Represent the trajectory of N data points by the approximating P^{th} order polynomial (for compression $P < N-1$).
- Represent the polynomial by its $P+1$ samples.
- We propose a vectorial form:
 - Apply to amplitude vectors.
 - Obtain $P+1$ representing vectors.
 - Adapt N and P per TD segment.



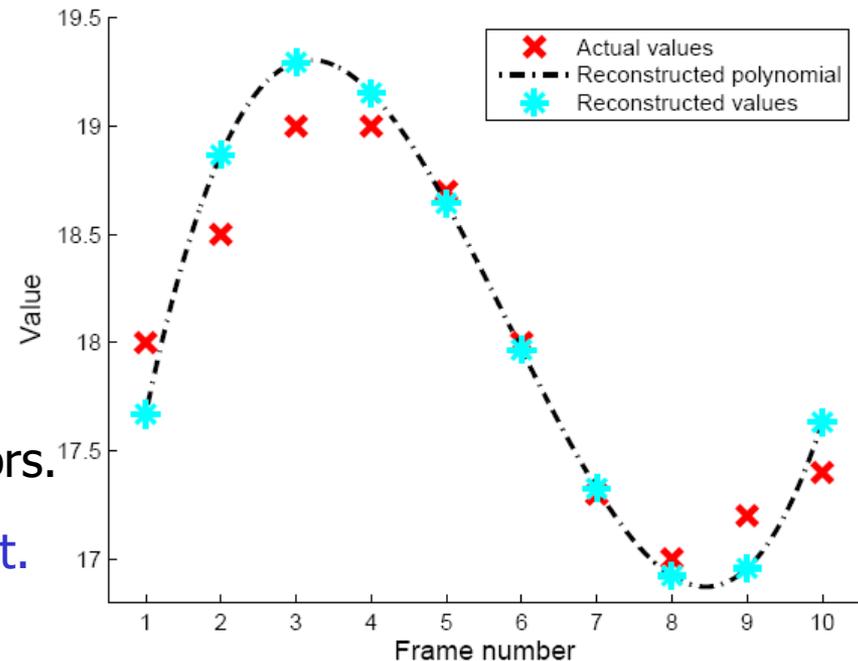
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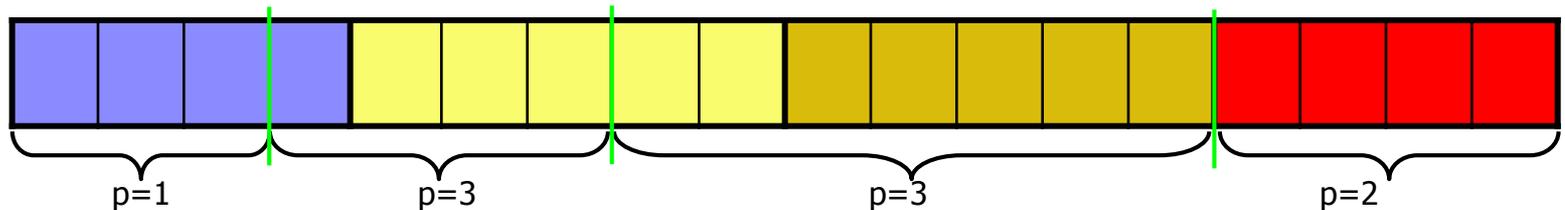
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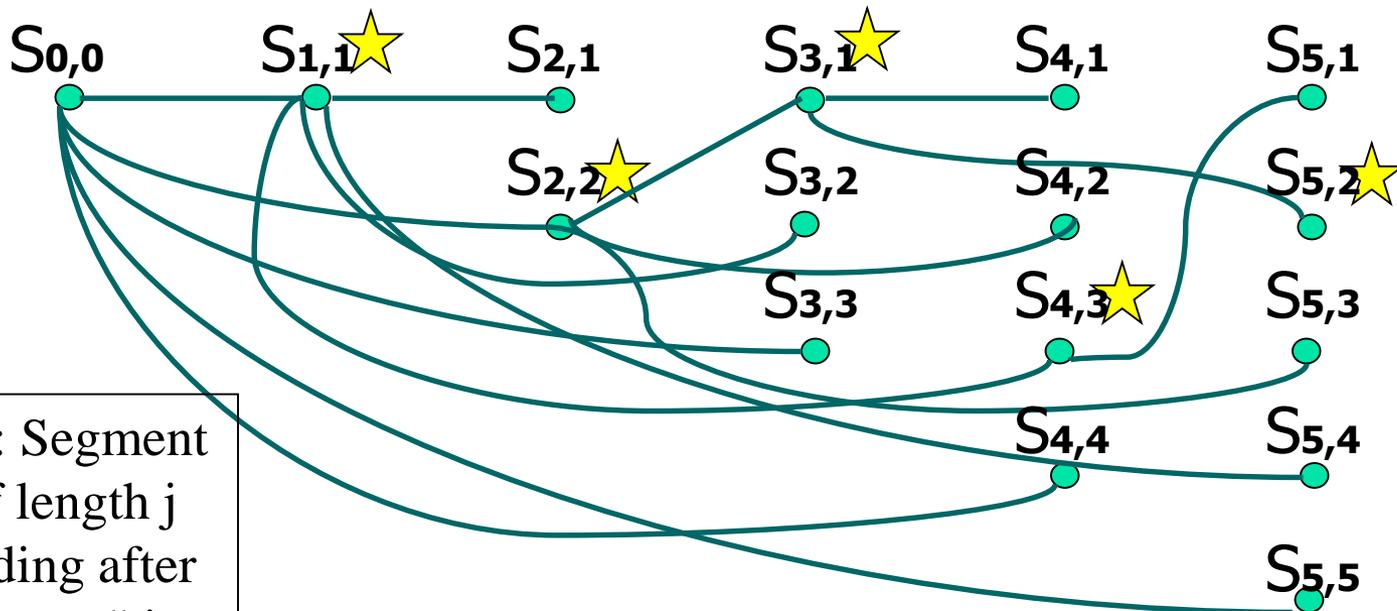
Polynomial TD for acoustic leaf

- Segments in each acoustic leaf are concatenated into a single 'super-segment'.
- Concatenation order is selected so that a cost function corresponding to the 'super-segment' smoothness is maximized.
- Smoothness criteria: WMSE between data & fitting pol. (order 2).
- Split 'super-segment' into short TD segments and fit each with a set of low order polynomials.



Segmentation and order selection

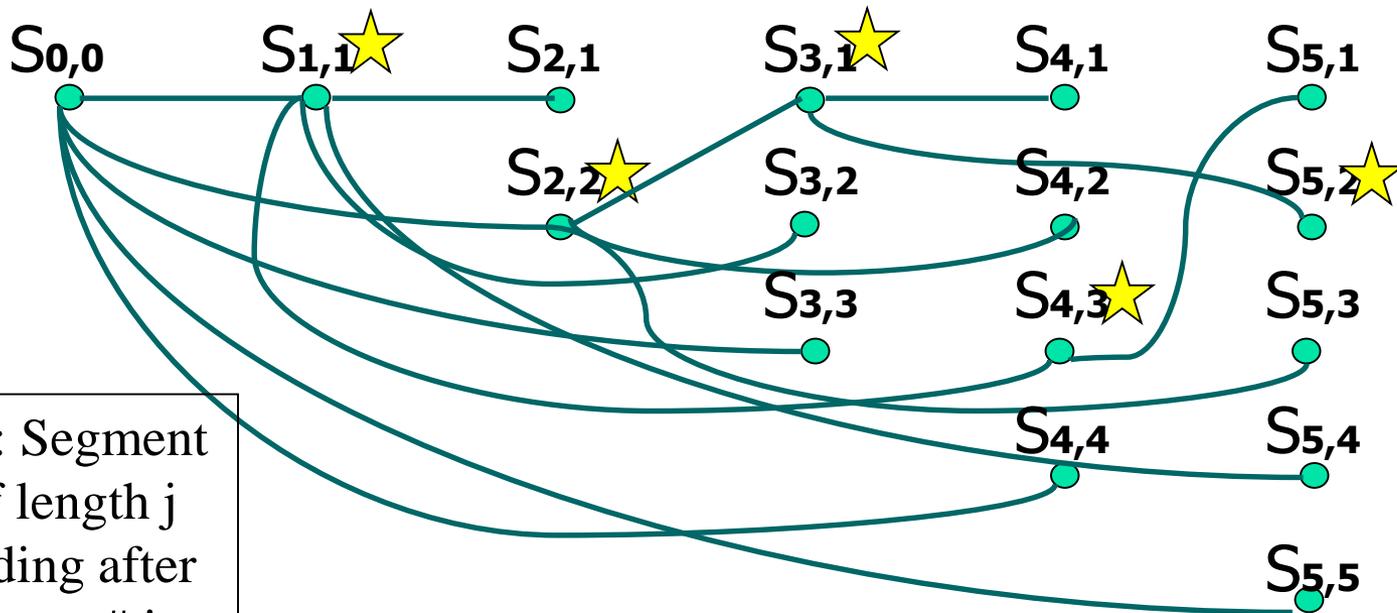
- Based on “R/D optimal linear prediction”, Prandoni *et al.* (2000).
- First, build graph with all possible segmentations.
- For each segment find lowest polynomial order that guarantees target **distortion**; assign a cost based on the corresponding **rate**.
- Find lowest cost path across graph using backtracking.



$S_{i,j}$: Segment
of length j
ending after
frame # i .

Segmentation and order selection

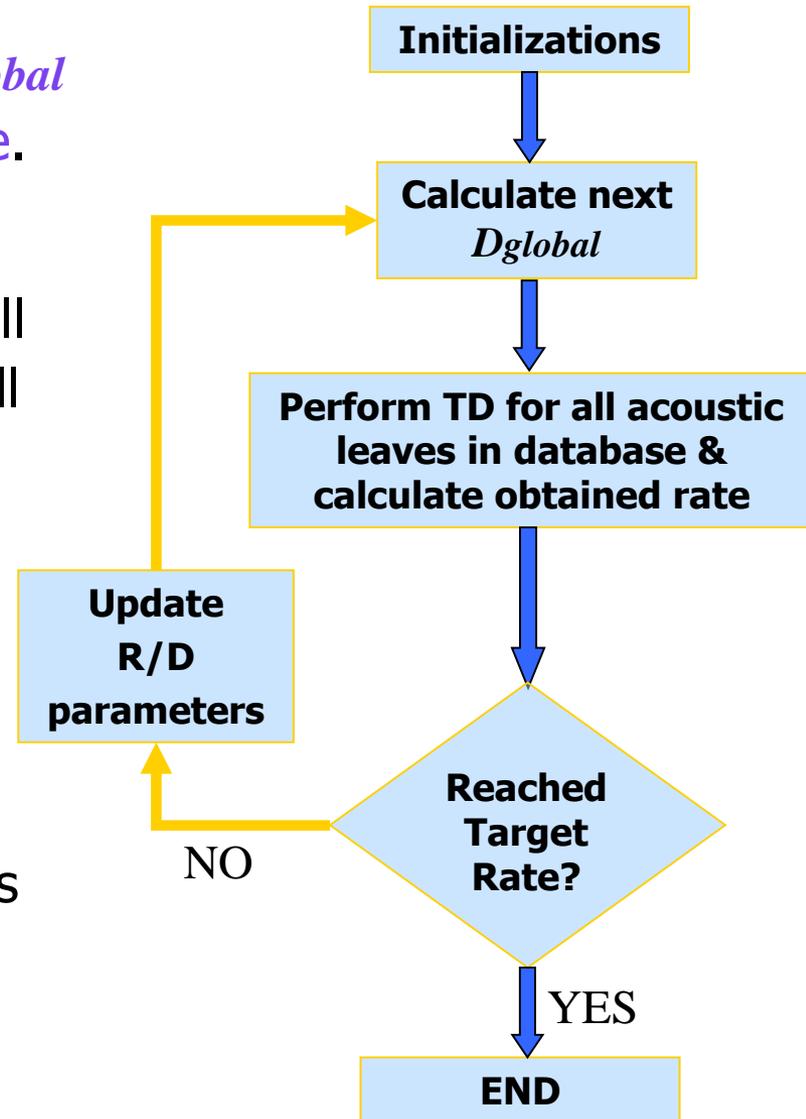
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Proposed Algorithm outline

- We seek the *minimum D_{global}* for which rate = *target rate*.
- *D_{global}* is the *maximum* allowed distortion among all frames in all segments in all leaves.
- For each candidate *D_{global}* value, we apply proposed polynomial TD to acoustic leaves.
- The calculated rate includes required overhead bits.



Some results

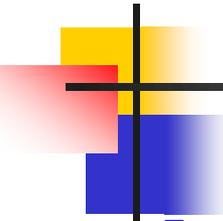
PESQ scores for recompression factor: x2

| Setup | | # | S.1 | S.2 | S.3 | S.4 | S.5 | S.6 | S.7 | S.8 | S.9 | S.10 | Avg. |
|------------|--------|---|------|------|------|------|------|------|------|------|------|------|-------------|
| Max Ord. 4 | No Reo | | 3.56 | 3.46 | 3.61 | 3.51 | 3.62 | 3.63 | 3.52 | 3.45 | 3.64 | 3.46 | 3.55 |
| | W. ReO | | 3.74 | 3.76 | 3.60 | 3.49 | 3.49 | 3.91 | 3.95 | 3.56 | 3.63 | 3.53 | 3.67 |
| Max Ord. 1 | No ReO | | 3.60 | 3.39 | 3.82 | 3.56 | 3.66 | 3.71 | 3.89 | 3.57 | 3.68 | 3.70 | 3.66 |
| | W. ReO | | 3.72 | 3.54 | 3.70 | 3.55 | 3.64 | 3.72 | 4.04 | 3.51 | 3.81 | 3.65 | 3.69 |

(*) For comparison: average PESQ for naïve down-sampling 2:1 is 2.84.

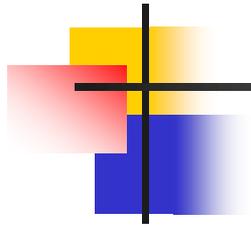
Samples:

| | Original | Max poly. order 4 | | Max poly. order 1 | |
|-----|---|---|---|---|---|
| | | No Reo | W.Reo | No Reo | W. Reo |
| S.8 |  |  |  |  |  |
| S.1 |  |  |  |  |  |



Summary

- We presented an algorithm for recompression of amplitude spectral parameters in a small footprint CTTS system, providing equivalent perceptual quality with a recompression factor of 2.
- We showed a vectorial form of polynomial TD used with jointly optimal sub-segmentation and polynomial order selection.
- Iterative algorithm converges to target rate with minmax distortion.
- Important feature: The compressed 'data' lies in the in the same space as the original data set.
- We applied the algorithm to a specific case, but it can be readily applied to a variety of (re) compression challenges.



Thank you