Utterance Selection for Optimizing Intelligibility of TTS Voices Trained on ASR Data

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Research Questions

2- and 4-hour Subsets Out of 83 Hours

- Can we repurpose ASR data to create TTS voices?
- Can we select training utterances to optimize intelligibility?
- Does automatic evaluation using ASR correlate with human judgments?

Feature	2hrs	4hrs
High mean energy	60.0	48.3
High stdv energy	83.1	64.6

Fast speaking rate 66.6 48.3

Hypo-articulation 64.6 49.1

48.0 45.1

MTurk

▲ Wit.ai

Watson

♦ Google

Middle stdv f0

Data and Tools

- **MACROPHONE:** short utterances read over the phone
 - ▷ Multiple speakers
 - ▷ Using 83 hours of female speech
 - ▷ Transcribed noise
- ► **HTS:** Toolkit for training HMM-based TTS voices
- Amazon Mechanical Turk (AMT): Crowdsourcing platform

Best voices:

- \blacktriangleright 4/83 and 2/83 hrs middle stdv f0
- ► 4/83 hrs fast speaking rate
- ► 4/83 hrs high mean energy
- ► 4/83 hrs hypo-articulated

Approach: Subset Selection

- **Baseline:** Train speaker-independent voice using first 10 hours of female data
- **Subsets:** Train voices only on subsets of the data, selected from high, medium, or low levels of various features:
 - Mean and standard deviation of f0 and energy
 - Speaking rate, level of articulation, and utterance length
 - Clipping, transcribed noise, spelled words
- **Evaluation:** Amazon Mechanical Turk

Automatic Evaluation Using ASR



Comparison of WERs from MTurk and ASR APIs



Constraint: Transcribers are allowed to evaluate a given sentence only once.

2-hour Subsets Out of 10 Hours

Baseline: **67.7%** WER

Feature	Low	Med	High
Mean f0	98.6	85.7	100.3
Stdv f0	83.1	80.0	87.1
Mean energy	98.6	95.7	70.6
Stdv energy	100.9	85.4	79.7
Speaking rate	-	99.1	54.3
Articulation	76.0	87.7	-
Utterance length	96.6	85.4	96.9

Voices

Eval	Correl (r)	Std.Dev (%)
MTurk		4.52
wit.ai	0.728	1.20
Watson	0.797	0.00
Google	0.876	0.00

Limitations:

- "Black box"
- Built for semantically sensible utterances
- Models may change

Removing Noise Out of 10 Hours

Subset	Hours	WER
3 or more words	7:34	79.7
No clipping	9:57	77.7
No transcribed noise	5:53	58.9
No spelled words	9:24	94.3

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http://www.cs.columbia.edu/speech SpeechLab@Columbia: