Machine Learning in Speech Synthesis

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Overview

- Speech Synthesis History and Overview
  - From hand-crafted to data-driven techniques
- Text to Speech Processes
- Waveform synthesis
  - Unit selection and Statistical Parametric Synthesis
- Evaluation
- Voice conversion

Physical Models

- Blowing air through tubes…

  - von Kemplen's synthesizer 1791

- Synthesis by physical models
  - Homer Dudley's Voder. 1939

More Computation – More Data

- *Formant synthesis (60s-80s)*
  - *Waveform construction from components*
- *Diphone synthesis (80s-90s)*
  - *Waveform by concatenation of small number of instances of speech*
- *Unit selection (90s-00s)*
  - *Waveform by concatenation of very large number of instances of speech*
- *Statistical Parametric Synthesis (00s-..)*
  - *Waveform construction from parametric models*

Waveform Generation

- Formant synthesis
- Random word/phrase concatenation
- Phone concatenation
- Diphone concatenation
- Sub-word unit selection
- Cluster based unit selection
- Statistical Parametric Synthesis

Speech Synthesis

- *Text Analysis*
  - *Chunking, tokenization, token expansion*
- *Linguistic Analysis*
  - *Pronunciations*
  - *Prosody*
- *Waveform generation*
  - *From phones and prosody to waveforms*

Text processing

- *Find the words*
  - *Splitting tokens too e.g. "04/11/2009"*
  - *Removing punctuation*
- *Identifying word types*
  - *Numbers: years, quantities, ordinals*
  - *1996 sheep were stolen on 25 Nov 1996*
- *Identifying words/abbreviations*
  - *CIA, 10m, 12sf, WeH7200*

Pronunciations

- *Giving pronunciation for each word*
  - *A phoneme string (plus tone, stress …)*
- *A constructed lexicon*
  - *(“pencil” n (p eh1 n s ih l))*
  - *(“two” n (t uw1))*
- *Letter to sound rules*
  - *Pronunciation of out of vocabulary words*
  - *Machine learning prediction from letters*

Pronunciation of Unknown Words

- *How do you pronounce new words*
- *4% of tokens (in news) are new*
- *You can't synthesis then without pronunciations*
- *You can't recognize them without pronunciations*
- *Letter-to-Sounds rules*
- *Grapheme-to-Phoneme rules*

LTS: Hand written

- *Hand written rules*
  - *[LeftContext] X [RightContext] -> Y*
  - *e.g.*
  - *c [h r] -> k*
  - *c [h] -> ch*
  - *c [i] -> s*
  - *c -> k*

LTS: Machine Learning Techniques

- *Need an existing lexicon*
  - *Pronunciations: words and phones*
  - *But different number of letters and phones*
- *Need an alignment*
  - *Between letters and phones*
  - *checked -> ch eh k t*

LTS: alignment

- checked -> ch eh k t

c	*h*	*e*	*c*	*k*	*e*	*d*
ch	*_*	*eh*	*k*	*_*	*_*	*t*

- Some letters go to nothing
- Some letters go to two phones
  - box -> b aa k-s
  - table -> t ey b ax-l -

Find alignment automatically

- *Epsilon scattering*
  - *Find all possible alignments*
  - *Estimate p(L,P) on each alignment*
  - *Find most probable alignment*
- *Hand seed*
  - *Hand specify allowable pairs*
  - *Estimate p(L,P) on each possible alignment*
  - *Find most probable alignment*
- *Statistical Machine Translation (IBM model 1)*
  - *Estimate p(L,P) on each possible alignment*
  - *Find most probably alignment*

Not everything aligns

- *0, 1, and 2 letter cases*
  - *e -> epsilon   "moved"*
  - *x -> k-s, g-z   "box" "example"*
  - *e -> y-uw   "askew"*
- *Some alignment aren't sensible*
  - *dept -> d ih p aa r t m ax n t*
  - *cmu -> s iy eh m y uw*

Training LTS models

- *Use CART trees*
  - *One model for each letter*
- *Predict phone (epsilon, phone, dual phone)*
  - *From letter 3-context (and POS)*
- *# # # c h e c -> ch*
- *# # c h e c k -> _*
- *# c h e c k e -> eh*
- *c h e c k e d -> k*

LTS results

- Split lexicon into train/test 90%/10%
  - i.e. every tenth entry is extracted for testing

Lexicon	*Letter Acc*	*Word Acc*
OALD	*95.80%*	*75.56%*
CMUDICT	*91.99%*	*57.80%*
BRULEX	*99.00%*	*93.03%*
DE-CELEX	*98.79%*	*89.38%*
Thai	*95.60%*	*68.76%*

Example Tree

```
For letter V:
if (n.name is v)
    return _
    if (n.name is #)
            if (p.p.name is t)
                return f
                return v
            if (n.name is s)
                if (p.p.p.name is n)
                    return f
                    return v
                return v
```

But we need more than phones

- What about lexical stress
  - p r aa1 j eh k t -> p r aa j eh1 k t
- Two possibilities
  - A separate prediction model
  - Join model – introduce eh/eh1 (BETTER)

	LTP+S	*LTPS*
L no S	*96.36%*	*96.27%*
Letter	*---*	*95.80%*
W no S	*76.92%*	*74.69%*
Word	*63.68%*	*74.56%*

Does it really work

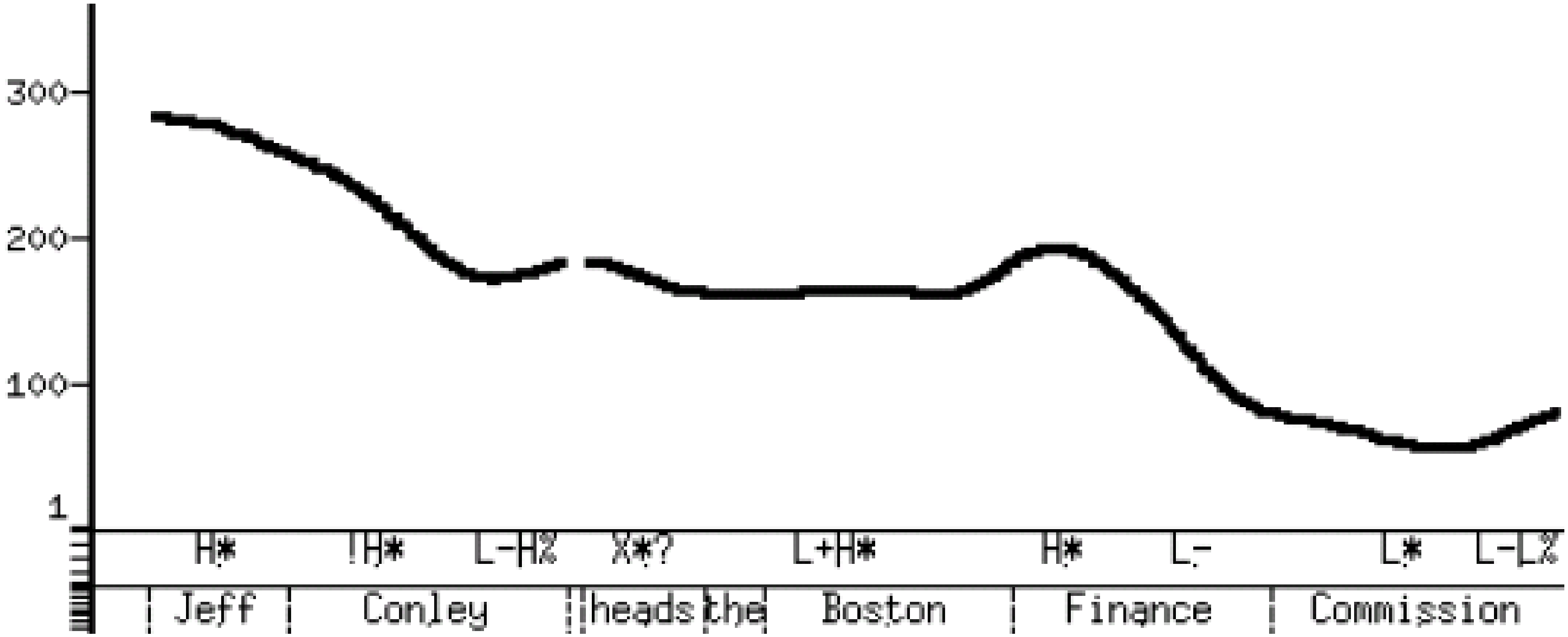
- 40K words from Time Magazine
  - 1775 (4.6%) not in OALD
  - LTS gets 70% correct (test set was 74%)

	Occurs	%
Names	1360	76.6
Unknown	351	19.8
US Spelling	57	3.2
Typos	7	0.4

Prosody Modeling

- *Phrasing*
  - *Where to take breaths*
- *Intonation*
  - *Where (and what size) are accents*
  - *F0 realization*
- *Duration*
  - *What is the length of each phoneme*

Intonation Contour



Unit Selection vs Parametric

Unit Selection

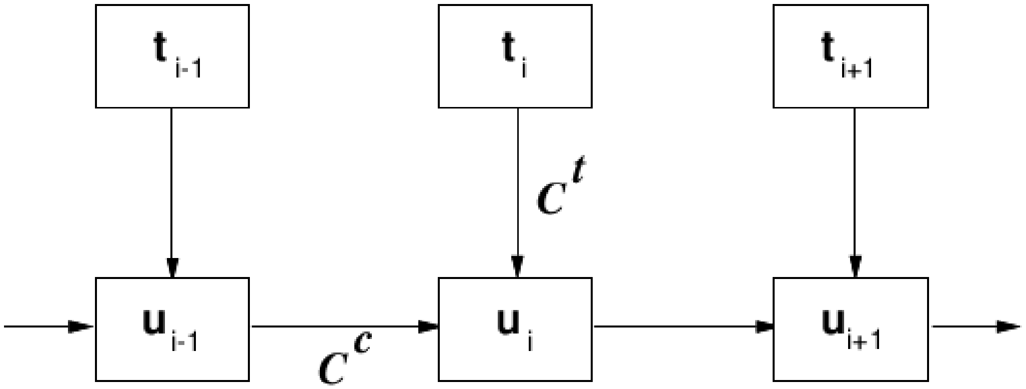
- The “standard” method
- “*Select appropriate sub-word units from large databases of natural speech*”

Parametric Synthesis: [NITECH: Tokuda et al]

- HMM-generation based synthesis
- Cluster units to form models
- Generate from the models
- “*Take ‘average’ of units*”

Unit Selection

- Target cost and Join cost [Hunt and Black 96]
  - Target cost is distance from desired unit to actual unit in the databases
    - Based on phonetic, prosodic metrical context
  - Join cost is how well the selected units join



“Hunt and Black” Costs

Target distance is:

– $C^t(t_i, u_i) = \Sigma_{j=1}^{p} w_j^t C_j^t(t_i, u_i)$

For examples *in the database* we can measure

– $AC^t(t_i, u_i)$

Therefore estimate w_{1-j} from all examples of

– $AC^t(t_i, u_i) \approx \Sigma_{j=1}^{p} w_j^t C_j^t(t_i, u_i)$

Use linear regression

How well does it join:

– $C^c(u_{i-1}, u_i) = \Sigma_{k=1}^{p} w_k^c C_k^c(u_{i-1}, u_i)$

– if $(u_{i-1} == \text{prev}(u_i))\ C^c = 0$

HB Unit Selection

Find best path of units through db that minimise:

$$C(t_1^n, u_1^n) = \Sigma_{i=1}^{n} C^t(t_i, u_i) + \Sigma_{i=2}^{n} C^c(u_{i-1}, u_i) + C^c(S, u_1) + C^c(u_n, S)$$

- Use Viterbi to find best set of units
- Note
  - Finding “longest” is typically not optimal

Clustering Units

- Cluster units [Donovan et al 96, Black et al 97]

$$Adist(U,V) = \begin{cases} \text{if } |V| > |U| & Adist(V,U) \\ \frac{WD*|U|}{|V|} * \sum_{i=1}^{|U|} \sum_{j=1}^{n} \frac{W_j.(abs(F_{ij}(U) - F_{(i*|V|/|U|)j}(V)))}{SD_j * n * |U|} \end{cases}$$

$|U|$ = number of frames in U
$F_{xy}(U)$ = parameter y of frame x of unit U
SD_j = standard deviation of parameter j
W_j = weight for parameter j
WD = duration penalty

- Moves calculation to compile time

Unit Selection Issues

- Cost metrics
  - Finding best weights, best techniques etc
- Database design
  - Best database coverage
- Automatic labeling accuracy
  - Finding errors/confidence
- Limited domain:
  - Target the databases to a particular application
  - Talking clocks
  - Targeted domain synthesis

Old vs New

Unit Selection:

- large carefully labelled database
- quality good when good examples available
- quality will sometimes be bad
- no control of prosody

Parametric Synthesis:

- smaller less carefully labelled database
- quality consistent
- resynthesis requires vocoder, (buzzy)
- can (must) control prosody
- model size much smaller than Unit DB

Parametric Synthesis

- Probabilistic Models

$$argmax(P(O|W))$$

- Simplification

$$argmax(P(o_0|W), P(o_1|W), ..., P(o_n|W))$$

- Generative model
  - Predict acoustic frames from text

Trajectories

- *Frame (State) based prediction*
  - *Ignores dynamics*
- *Various solutions*
  - *MLPG (maximum likelihood parameter generation)*
  - *Trajectory HMMs*
  - *Global Variance*
  - *MGE, minimal generation error*

SPSS Systems

- *HTS (NITECH)*
  - *Based on HTK*
  - *Predicts HMM-states*
  - *(Default) uses MCEP and MLSA filter*
  - *Supported in Festival*
- *Clustergen (CMU)*
  - *No use of HTK*
  - *Predicts Frames*
  - *(Default) uses MCEP and MLSA filter*
  - *More tightly coupled with Festival*

Synthesizer

Requires:
- Prompt transcriptions (txt.done.data)
- Waveform files (well recorded)

FestVox Labelling
- EHMM (Kishore)
- Context Independent models and forced alignment
- (Have used Janus labels too).

Parameter extraction:
- (HTS's) melcep/mlsa filter for resynthesis
- F0 extraction

Clustering
- Wagon vector clustering
- for each HMM-state name

Clustering by CART

Update to Wagon (Edinburgh Speech Tools).

- Tight coupling of features with FestVox utts
- Support for arbitrary vectors
- Define impurity on clusters of *N* vectors

$$\left(\sum_{i=1}^{24} \sigma_i\right) * N$$

Clustering

- F0 and MCEP
- Tested jointly and separately
- Features for clustering (51):
  - phonetic, syllable, phrasal context

Training Output

Three models:

- Spectral (MCEP) CART tree
- F0 CART tree
- Duration CART tree

F0 model:

- Smoothed extracted F0 through all speech
- (i.e. unvoiced regions get F0 values)
- Chose voicing at runtime phonetically

CLUSTERGEN Synthesis

Generate phoneme strings (as before)

For each phone:

- Find HMM-state names: ah_1, ah_2, ah_3
- Predict duration of each
- Create empty mcep vector to fill duration
- Predict mcep values from cluster tree
- Predict F0 value from cluster tree

Use MLSA filter to regenerate speech

Objective Score

CLUSTERGEN

Mean Mel Cepstral Distortion over test set

$$10/\ln 10\sqrt{2\sum_{d=1}^{24}\left(mc_d^{(t)} - mc_d^{(e)}\right)^2}$$

MCD: Voice Conversion ranges 4.5-6.0

MCD: CG scores 4.0-8.0

smaller is better

Example CG Voices

7 Arctic databases:

1200 utterances, 43K segs, 1hr speech

awb	bdl
clb	jmk
ksp	rms
slt	

Database size vs Quality

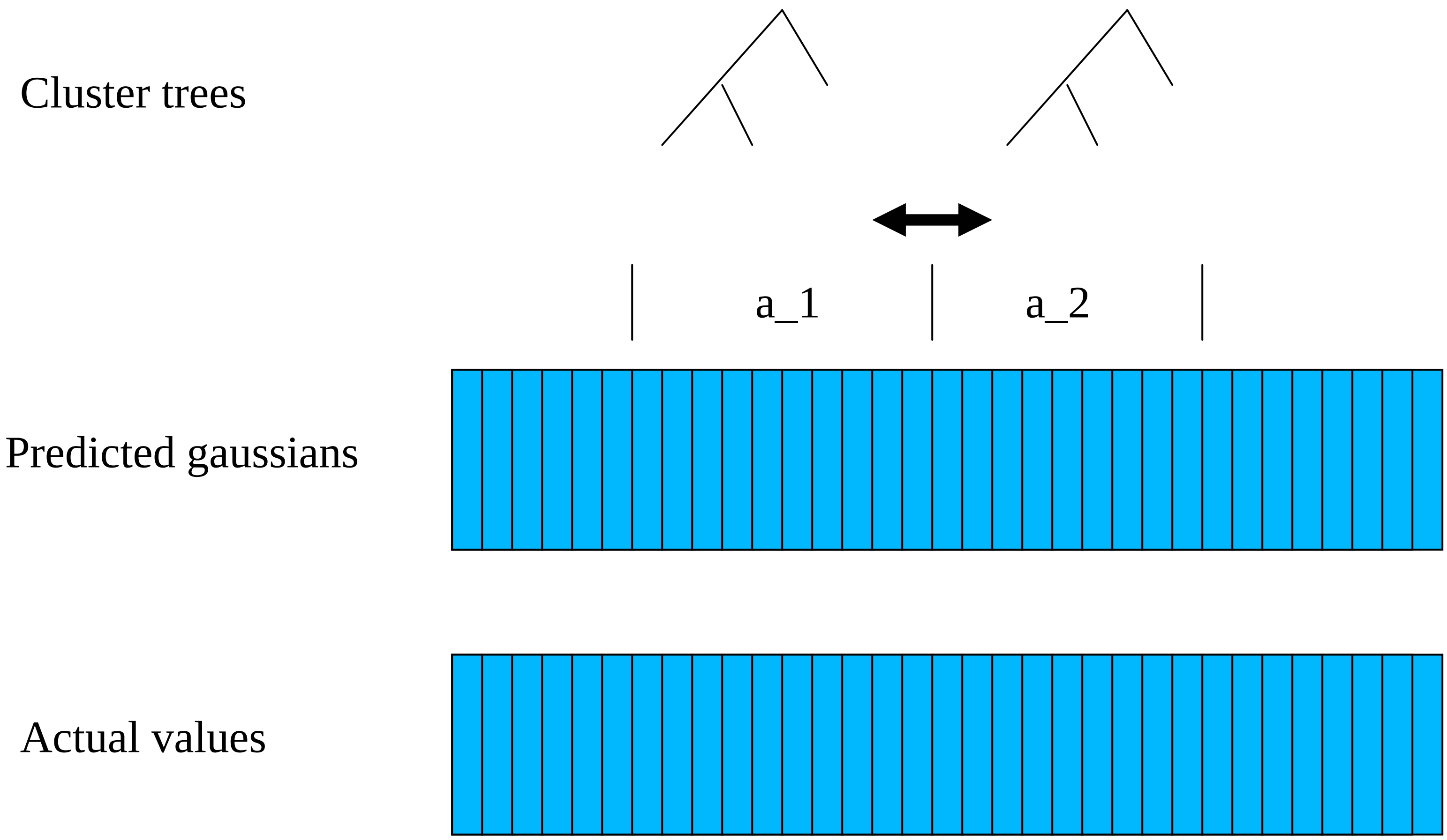
slt_arctic data size

Utts	*Clusters*	*RMS F0*	*MCD*	
50	*230*	*24.29*	*6.761*	
100	*435*	*19.47*	*6.278*	
200	*824*	*17.41*	*6.047*	
500	*2227*	*15.02*	*5.755*	
1100	*4597*	*14.55*	*5.685*	

Making it Better

- *Label data, build model*
- *But maybe there are better labels*
- *So find labels that maximize model accuracy*

Move Labels



Move Labels

- *Use EHMM to label segments/HMM states*
- *Build Clustergen Model*
- *Iterate*
  - *Predict Cluster (mean/std) for each frame*
  - *For each label boundary*
    - *If dist(actual_after,pred_before) < dist(actual_after,pred_after)*
      - *Move label forward*
    - *If dist(actual_before,pred_after) < dist(actual_before,pred_before)*
      - *Move label backward*

Distance Metric

- *Distance from predicted to actual*
  - *Euclidean*
  - *F0, static, deltas, voicing*
  - *With/without standard deviation normalization*
  - *Weighting*
- *Best choice*
  - *Static without stddev normalization*
  - *(This is closest to MCD)*

ML with 10 iterations

- rms voice (66 minutes of speech)
  - train 1019 utts, test 113 utts (every tenth)

Pass	Move	+ve	-ve	MCD	stddev	F0
0	0	0	0	5.247	1.965	13.990
1	48211	23162	25949	5.121	1.846	14.251
2	40731	20223	20508	5.090	1.794	14.220
3	35059	17835	17224	5.073	1.779	14.267
4	33083	16503	16580	5.061	1.765	14.260
5	31131	15518	15613	5.046	1.753	14.306
6	29693	14813	14880	5.042	1.754	14.287
7	28361	14143	14218	5.042	1.757	14.240
8	27571	13730	13841	**5.035**	1.740	14.239
9	26839	13457	13382	5.040	1.750	14.187

Move Labels

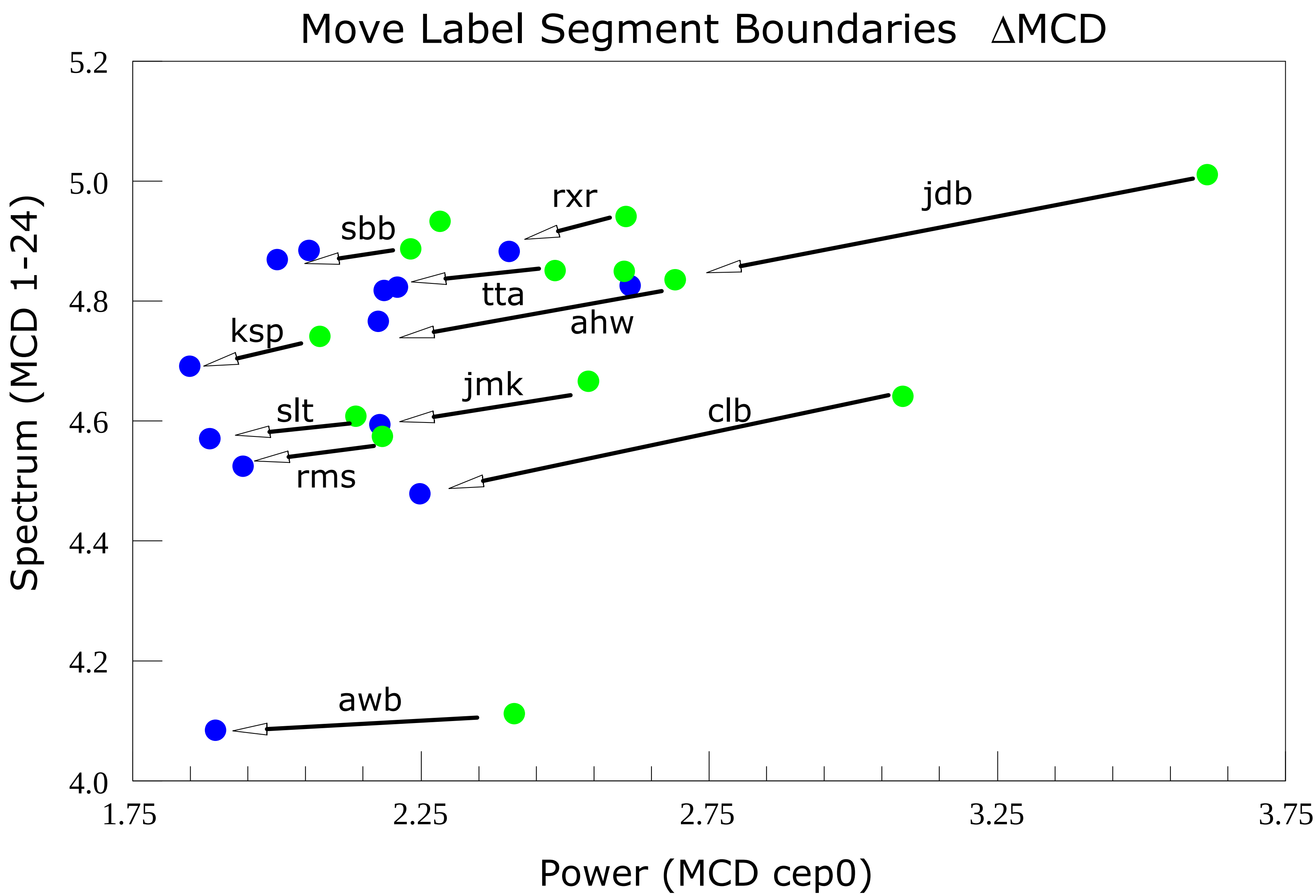
Voice	*2006*	*2008 base*	*2008 ml*
ahw	-	*5.234*	*5.057*
awb	*6.557*	*4.445*	*4.483*
bdl	*6.129*	*5.685*	*5.467*
clb	*5.417*	*4.838*	*4.698*
jmk	*6.165*	*5.398*	*5.239*
ksp	*5.980*	*5.289*	*5.140*
rms	*5.731*	*5.247*	*5.035*
rxr	-	*5.298*	*5.160*
slt	*5.713*	*5.170*	*4.983*

Average improvement 0.172 (excluding awb)

Does it **sound** better

- rms
  - abtest (10 utterances)
    - **ml** 7
    - **base** 1
    - **=** 2
- Slt base ml
  - abtest
    - **ml** 7
    - **base** 2
    - **=** 1

Arctic MLSB improvements



Grapheme Based Synthesis

- *Synthesis without a phoneme set*
- *Use the letters as phonemes*
  - *(“alan” nil (a l a n))*
  - *(“black” nil (b l a c k))*
- *Spanish (easier ?)*
  - *419 utterances*
  - *HMM training to label databases*
  - *Simple pronunciation rules*
  - *Polici’a -> p o l i c i’ a*
  - *Cuatro -> c u a t r o*

Spanish Grapheme Synthesis

Word	Castillian	gloss
casa	/**k** a s a/	house
cesa	/**th** e s a/	stop
cine	/**th** i n e/	cinema
cosa	/**k** o s a/	thing
cuna	/**k** u n a/	cradle
he**c**hizo	/e **ch** i th o/	charm, spell

In Spanish the letter "c" may be pronounced /k/, /ch/ and /th/ or /s/ (depending on dialect). The choice of phone is determined by the letter context.

English Grapheme Synthesis

- Use Letters are phones
- 26 “phonemes”
  - (“alan” n (a l a n))
  - (“black” n (b l a c k))
- Build HMM acoustic models for labeling
- For English
  - “This is a pen”
  - “We went to the church at Christmas”
  - Festival intro
  - “do eight meat”
- Requires method to fix errors
  - Letter to letter mapping

Common Data Sets

- *Data drive techniques need data*
- *Diphone Databases*
  - *CSTR and CMU US English Diphone sets (kal and ked)*
- *CMU ARCTIC Databases*
  - *1200 phonetically balanced utterances (about 1 hour)*
  - *7 different speakers (2 male 2 female 3 accented)*
  - *EGG, phonetically labeled*
  - *Utterances chosen from out-of-copyright text*
  - *Easy to say*
  - *Freely distributable*
  - *Tools to build your own in your own language*

Blizzard Challenge

- *Realistic evaluation*
  - *Under the same conditions*
- *Blizzard Challenge [Black and Tokuda]*
  - *Participants build voice from common dataset*
  - *Synthesis test sentences*
  - *Large set of listening experiments*
  - *Since 2005, now in 7th year*
  - *18 groups in 2010*
  - *Audio books in 2012*

How to test synthesis

- *Blizzard tests:*
  - *Do you like it? (MOS scores)*
  - *Can you understand it?*
    - *SUS sentence*
    - *The unsure steaks overcame the zippy rudder*
- *Can't this be done automatically?*
  - *Not yet (at least not reliably enough)*
  - *But we now have lots of data for training techniques*
- *Why does it still sound like robot?*
  - *Need better (appropriate testing)*

SUS Sentences

- *sus_00022*
- *sus_00012*
- *sus_00005*
- *sus_00017*

SUS Sentences

- *The serene adjustments foresaw the acceptable acquisition*
- *The temperamental gateways forgave the weatherbeaten finalist*
- *The sorrowful premieres sang the ostentatious gymnast*
- *The disruptive billboards blew the sugary endorsement*

Voice Identity

- *What makes a voice identity*
  - *Lexical Choice:*
    - *Woo-hoo,*
    - *I pity the fool …*
  - *Phonetic choice*
  - *Intonation and duration*
  - *Spectral qualities (vocal tract shape)*
  - *Excitation*

Voice Conversion techniques

- *Full ASR and TTS*
  - *Much too hard to do reliably*
- *Codebook transformation*
  - *ASR HMM state to HMM state transformation*
- *GMM based transformation*
  - *Build a mapping function between frames*

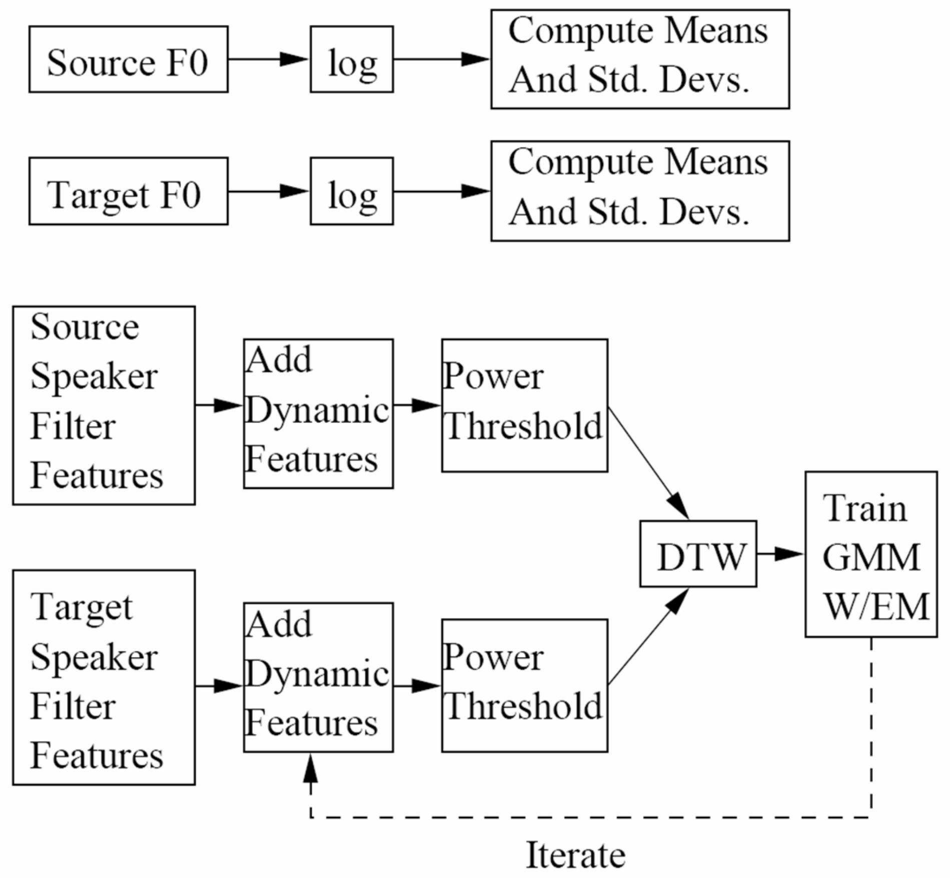
Learning VC models

- *First need to get parallel speech*
  - *Source and Target say same thing*
  - *Use DTW to align (in the spectral domain)*
  - *Trying to learn a functional mapping*
  - *20-50 utterances*
- *"Text-independent" VC*
  - *Means no parallel speech available*
  - *Use some form of synthesis to generate it*

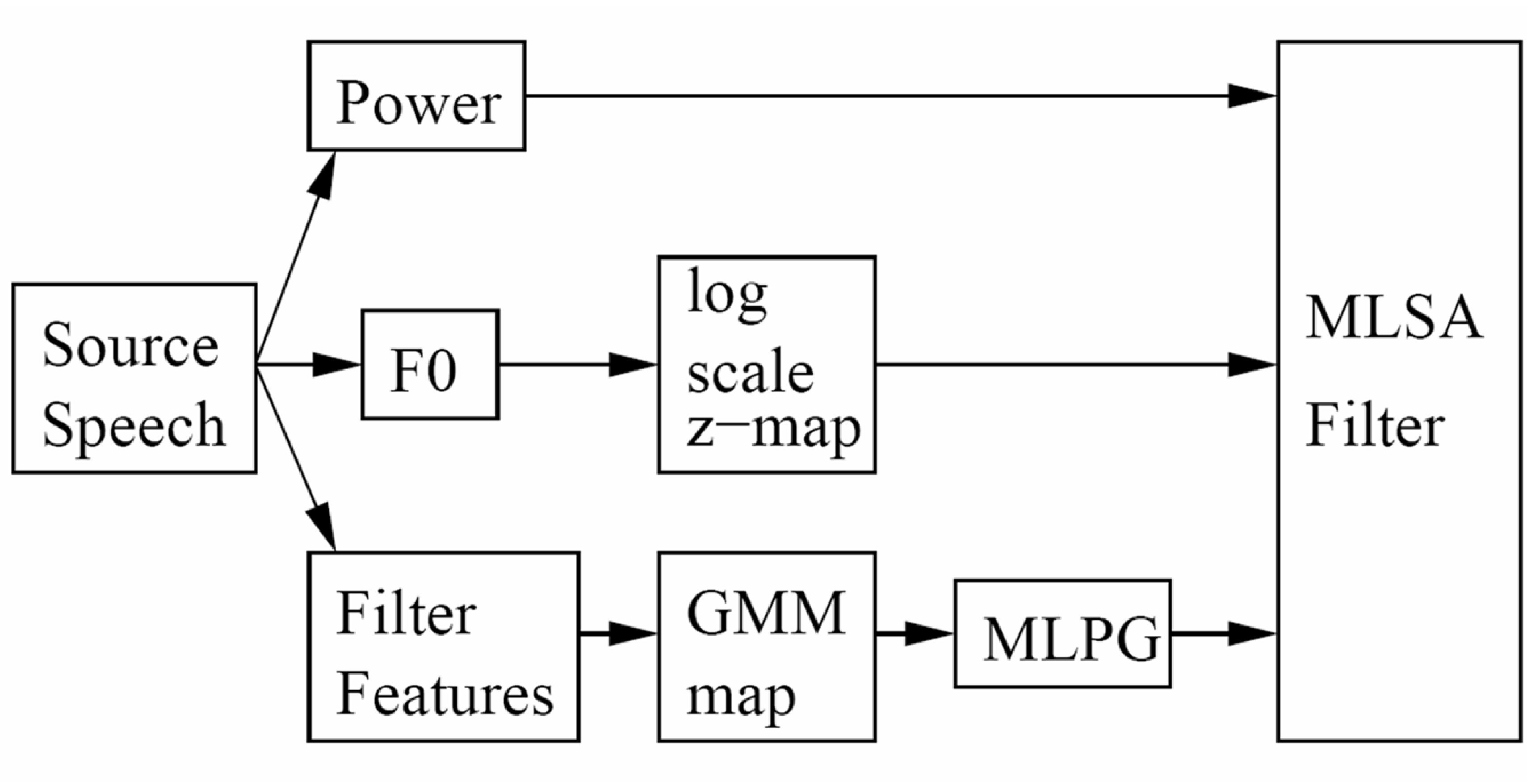
VC Training process

- *Extract F0, power and MFCC from source and target utterances*
- *DTW align source and target*
- *Loop until convergence*
  - *Build GMM to map between source/target*
  - *DTW source/target using GMM mapping*

VC Training process



VC Run-time


Power
Source Speech
F0
log scale z−map
Filter Features
GMM map
MLPG
MLSA Filter

Voice Transformation

- Festvox GMM transformation suite (Toda)

	awb	bdl	jmk	slt
awb				
bdl				
jmk				
slt				

VC in Synthesis

- *Can be used as a post filter in synthesis*
  - *Build kal_diphone to target VC*
  - *Use on all output of kal_diphone*
- *Can be used to convert a full DB*
  - *Convert a full db and rebuild a voice*

Style/Emotion Conversion

- *Unit Selection (or SPS)*
  - *Require lots of data in desired style/emotion*
- *VC technique*
  - *Use as filter to main voice (same speaker)*
  - *Convert neutral to angry, sad, happy …*

Can you say that again?

- *Voice conversion for speaking in noise*
- *Different quality when you repeat things*
- *Different quality when you speak in noise*
  - *Lombard effect (when very loud)*
  - *“Speech-in-noise” in regular noise*

Speaking in Noise (Langner)

- *Collect data*
  - *Randomly play noise in person's ears*
  - *Normal*
  - *In Noise*
- *Collect 500 of each type*
- *Build VC model*
  - *Normal -> in-Noise*
- *Actually*
  - *Spectral, duration, f0 and power differences*

Synthesis in Noise

- *For bus information task*
- *Play different synthesis information utts*
  - *With SIN synthesizer*
  - *With SWN synthesizer*
  - *With VC (SWN->SIN) synthesizer*
- *Measure their understanding*
  - *SIN synthesizer better (in Noise)*
  - *SIN synthesizer better (without Noise for elderly)*

Transterpolation

- *Incrementally transform a voice X%*
  - *BDL-SLT by 10%*
  - *SLT-BDL by 10%*
- *Count when you think it changes from M-F*
- *Fun but what are the uses …*

De-identification

- *Remove speaker identity*
  - *But keep it still human like*
- *Health Records*
  - *HIPAA laws require this*
  - *Not just removing names and SSNs*
- *Remove identifiable properties*
  - *Use Voice conversion to remove spectral*
  - *Use F0/duration mapping to remove prosodic*
  - *Use ASR/MT techniques to remove lexical*

Summary

- *Data-driven speech synthesis*
  - *Text processing*
  - *Prosody and pronunciation*
  - *Waveform synthesis*
- *Finding the right optimization*
  - *Find an objective metric that correlates with human perception*