Phoneme and Sub-phoneme T-Normalization for Text-Dependent Speaker Recognition

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IEEE Odyssey 2008, Cape Town, South Africa, 21-24 Jan 08

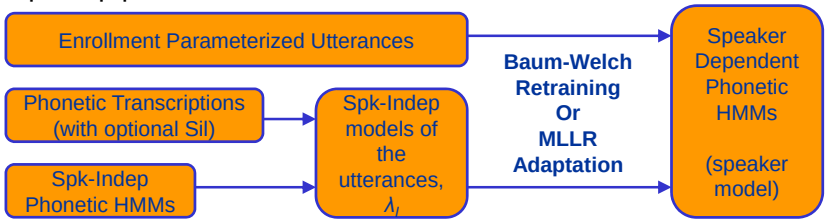
Outline

1. Introduction

- Text-Independent Speaker Recognition
  - Unknown linguistic content
  - Research driven by yearly NIST SRE evals
- Text-Dependent Speaker Recognition
  - Linguistic content of test utterance known by system
    - Password set by the user
      - Security based on password + speaker recognition
    - Text prompted by the system
      - Security based on speaker recognition only
  - No competitive evaluations by NIST
  - YOHO is one of the most extended databases for experimentation
- This work is on **text prompted systems** with YOHO as test database

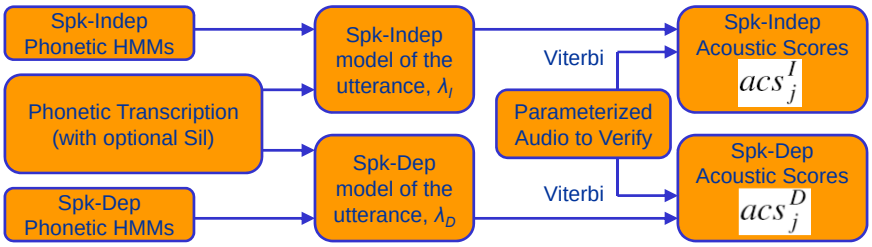
2.1. Text-dependent SR based on phonetic HMMs: Enrollment Phase

- Speech parameterization (common to enrollment and test)
  - 25 ms Hamming windows with 10 ms window shift
  - 13 MFCCs + Deltas + Double Deltas → 39 coeffs
- Spk-indep, context-indep phonetic HMMs used as base models
  - 39 phones trained on TIMIT, 3 states left-to-right, 1-80 Gauss/state
- Spk-dep phonetic HMMs from transcribed enrollment audio



2.1. Text-dependent SR based on phonetic HMMs: Verification Phase

- Computation of acoustic scores for spk-dep and spk-indep models



- Acoustic scores → Verification score ($sc_2(\mathbf{O},\lambda_D)$ removing silences)

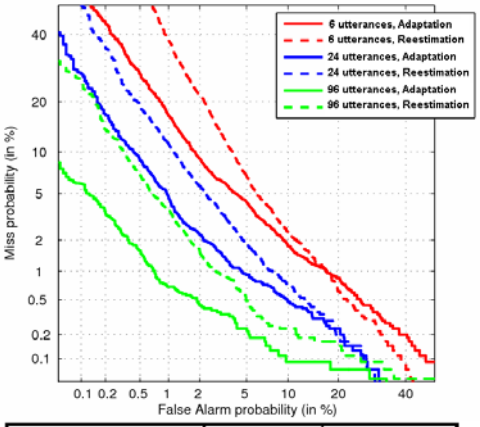
$$sc_1(\mathbf{O},\lambda_D)=\frac{1}{N}\left(\sum_{i=1}^{N} acs_i^D-\sum_{i=1}^{N} acs_i^I\right) \Rightarrow sc_2(\mathbf{O},\lambda_D)=\frac{1}{N_D^*}\sum_{\substack{i=1\\ pt_i^D\notin SIL}}^{K_D}\sum_{j=pt_{i-1}^D}^{pt_i^D-1} acs_j^D-\frac{1}{N_I^*}\sum_{\substack{i=1\\ pt_i^I\notin SIL}}^{K_I}\sum_{j=pt_{i-1}^I}^{pt_i^I-1} acs_j^I$$

2.2. Experimental Framework (YOHO)

- YOHO database
  - 138 speakers (106 male, 32 female)
    - Enrollment data: 4 sessions x 24 utterances = 96 utterances
    - Test data: 10 sessions x 4 utterances = 40 utterances
  - Utterance = 3 digit pairs (i.e. “twelve thirty four fifty six”)
- Usage of YOHO in this work
  - Enrollment: 3 different conditions
    - 6 utterances from the 1st enrollment session
    - 24 utterances from the 1st enrollment session
    - 96 utterances from the 4 enrollment sessions
  - Test: always with a single utterance
    - Target trials: 40 test utterances for each speaker (138 x 40 = 5,520)
    - Non-tgt trials: 137 test utterances for each speaker (138 x 137 = 18,906)
      - One random utterance from the test data of each of the other users

2.3. Results with raw scores

- DET curves and %EERs with raw scores comparing
  - Baum-Welch Re-estimation vs. MLLR Adaptation
    - For optimum configuration of tuning parameters in each case (Gauss/state, regression classes, re-estimation passes)
  - Different amounts of enrollment material
    - 6, 24 or 96 utterances
- MLLR Adaptation provides better performance for all conditions
- Our baseline for this work is the curve for MLLR adaptation with 6 utterances



Enrolment utterances (and sessions)	MLLR Adaptation	Baum-Welch Re-estimation
6 (1 session)	4,6	5,6
24 (1 session)	2,1	3,2
96 (4 sessions)	0,9	1,9

3. T-Norm in Text-Dependent SR

- T-Norm in Text-Independent SR
  - Regularly applied with excellent results
  - Normalize each score w.r.t. distribution of non-target scores for
    - The same test segment
    - A cohort of impostor speaker models
- T-Norm in Text-Dependent SR
  - Rarely applied with only modest improvement
  - A few notable exceptions are
    - [M. Hébert and D. Boies, ICASSP'05], where T-Norm is the main focus and
    - [R.D. Zylca et al., Odyssey'04], where T-Norm is applied but is not the main focus

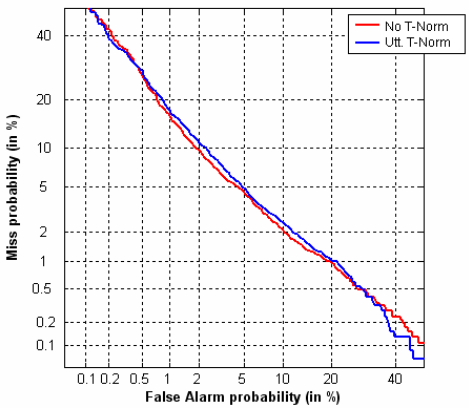
3.1. Plain (Utterance-level) T-Norm: Procedure

- Procedure in text-dependent SR is identical to T-Norm in text-independent SR
  - We call this Plain T-Norm or Utterance-level T-Norm to distinguish it from the other methods we propose
- 1. Compute verification scores for the same test utterance and a cohort of impostor speaker models:
  - Reserve a cohort of impostor speakers *{1, …, M}*
  - Obtain MLLR speaker-adapted phonetic HMMs for those speakers
  - Compute verification scores for the same test utterance and those speaker models $\{sc_2(\mathbf{O},\lambda_D^1), sc_2(\mathbf{O},\lambda_D^2),...,sc_2(\mathbf{O},\lambda_D^M)\}$
- 2. Normalize the verification score using the mean and standard deviation of the impostor scores obtained

$$sc_2^{TNorm}(\mathbf{O},\lambda_D) = \frac{sc_2(\mathbf{O},\lambda_D) - \mu_C^O}{\sigma_C^O}$$

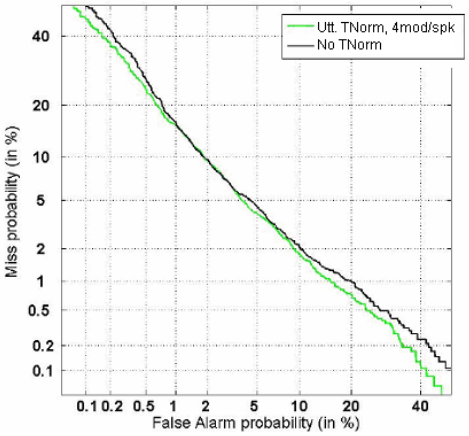
3.1. Plain (Utterance-level) T-Norm: Results (i)

- Plain (Utterance-level) T-Norm vs. No T-Norm on YOHO
  - Enrollment with only 6 utterances from 1 session and test with 1 utterance
  - 10 male and 10 female speakers reserved as cohort and not included in results
  - Cohort = 20 speaker models
  - MLLR adaptation
- Utterance-level T-Norm (Plain T-Norm) produces slightly worse results than doing nothing
- Perhaps due to very small cohort?



3.1. Plain (Utterance-level) T-Norm: Results (ii)

- Perhaps due to very small cohort?
- New experiment using a bigger cohort of models
  - But not speakers due to very limited amount of speakers in YOHO (32 f)
  - 4 speaker models by speaker in the cohort
  - Trained with the first 6 utterances in each session
- Slightly better results, but still the improvement achieved by T-Norm is very small
- Probably not only due to the small cohort



3.1. Plain (Utterance-level) T-Norm: Results (iii)

- Other causes for limited performance of T-Norm?
  - M. Hébert and D. Boies, (ICASSP'05) analyzed the effect of lexical mismatch, and proposed it as a cause for the poor performance
    - Smoothing mechanism that weighted the effect of T-Norm according to the goodness of the cohort to model the utterance to verify
- Could we reduce the effect of the lexical mismatch in other ways?
  - Reducing the lexical content of the test speech used to produce a speaker verification score to a single phoneme or sub-phoneme
  - And then T-Normalizing these scores and combining them
- Basic idea of Phoneme and Sub-phoneme-level T-Norm

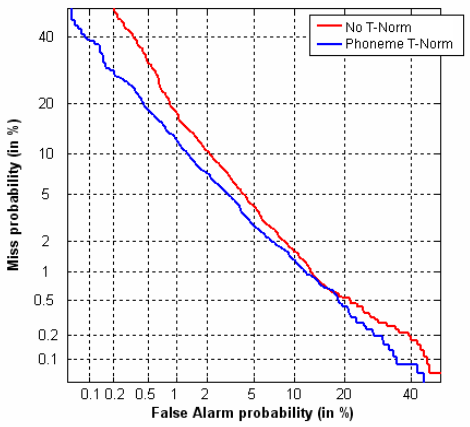
3.2. Phoneme-level T-Norm: Procedure

- Compute *phoneme-based verification scores* for the same test utterance, the speaker model and a cohort of impostor models
  - Compute a verification score for each non-silence phoneme *i*, $sc_p(\mathbf{O}, \lambda_D, i)$
    - Considering only acoustic scores associated to phoneme *i* in the utterance
  - Reserve a cohort of impostor speakers *{1, …, M}*
  - Obtain MLLR speaker-adapted phonetic HMMs for those speakers
  - For each non-silence phoneme, *i*, compute verification scores for the same test utterance and those speaker models $sc_p(\mathbf{O}, \lambda_D^1, i), \ldots, sc_p(\mathbf{O}, \lambda_D^M, i)$
- Normalize each phoneme-based verification score using the mean and standard deviation of the corresponding impostor scores obtained
- Combine normalized phoneme-based verification scores to form utterance verification score (taking into account phoneme lengths)

$$sc_2(\mathbf{O}, \lambda_D) \approx sc_p(\mathbf{O}, \lambda_D) = \frac{1}{N^*}\left(\sum_{i=1}^{K} N^*(i) sc_p(\mathbf{O}, \lambda_D, i)\right)$$

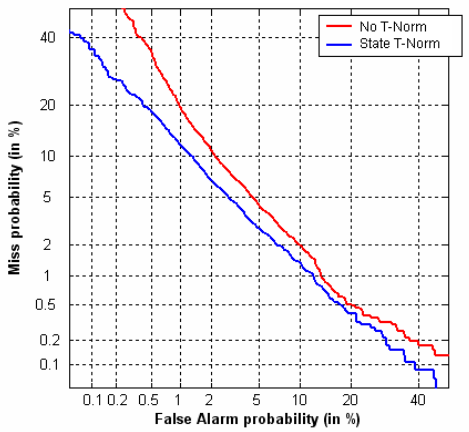
3.2. Phoneme-level T-Norm: Results

- Phoneme-level T-Norm vs. No T-Norm on YOHO
  - Enrolment with only 6 utterances from 1 session and test with 1 utterance
  - 10 male and 10 female speakers reserved as cohort and not included in results
  - Cohort = 20 speaker models
  - MLLR adaptation
- Phoneme-Level T-Norm is clearly better than No T-Norm
- Also clearly better than Utterance-Level T-Norm
- Can we do it better by using even smaller units?



3.3. Subphoneme-level T-Norm: Procedure & Results

- Using exactly the same idea of phoneme-level T-Norm
  - But using HMM states instead of phonemes
- State-level T-Norm vs. No T-Norm on YOHO
  - Enrolment with only 6 utterances from 1 session and test with 1 utterance
  - 10 male and 10 female speakers reserved as cohort and not included in results
  - Cohort = 20 speaker models
  - MLLR adaptation
- Results are even better than with Phoneme-level T-Norm



4. Summary of Results

Type of T-Norm	EER (%) (Rel. Improv. %)	FR@FA=1% (%) (Rel. Improv. %)
No T-Norm	4.82% (0.0%)	16.28% (0.0%)
Utterance-based	5.01% (-3.9%)	17.45% (-7.2%)
Phoneme-based	3.91% (18.9%)	12.17% (25.2%)
State-based	3.85% (20.1%)	11.81% (27.5%)

- Utterance-level T-Norm performs worse than doing nothing
- But the newly proposed Phoneme-level and State-level T-Norm provide relative improvements in EER close to 20% and over 25% in FR@FA=1%

5. Discussion (i)

- Phoneme and State-level T-Norm work clearly better than Utterance-level T-Norm in text-dependent SR
  - Utterance-level (or Plain) T-Norm suffers from lexical mismatch
- But this mismatch is *not* totally avoided by Phoneme or State-level T-Norm
  - It is still possible to have substantial differences in lexical content
  - However, now each phoneme/sub-phoneme in the test utterance produces an independent speaker verification score
    - For which the mismatch is limited to the mismatch in a single phoneme/sub-phoneme in the training material
  - This may reduce the influence of the lexical mismatch on the phoneme/sub-phoneme verification scores
  - Making T-Norm less sensitive to this problem

5. Discussion (ii)

- Other possible reason for the good performance of phoneme and state-level T-Norm
  - Based on ideas from a recent paper [Subramanya et al., ICASSP'07]
    - Subramanya computes speaker verification scores for each phoneme
    - And considers those scores as produced by independent weak speaker recognizers
    - That are combined using boosting to yield improved performance
  - This is (conceptually) similar to our approach
    - We combine phoneme or sub-phoneme verification scores
    - Weighting them according to their means and variances on a cohort
- Different phonemes/sub-phonemes → different discriminating powers
  - T-Norm at the phoneme or sub-phoneme levels could be able to weight them appropriately

6. Conclusions

- Applying T-Norm in text-dep SR the way we do in text-indep SR does not work well
  - This is Plain or Utterance-level T-Norm
- Newly proposed T-Norm schemes working at sub-utterance levels work much better
  - Phoneme-level T-Norm
  - Subphoneme-level T-Norm
- Possible reasons
  - Reduction of the effect of lexical mismatch
  - Better weighting/fusion of the information provided by the different phonemes or subphonemes

Thanks!

IEEE Odyssey 2008, Cape Town, South Africa, 21-24 Jan 08

Additional Slides

Baum-Welch Reestimation (YOHO)

		Gaussians / State				
		1	2	3	4	5
number of iterations	1	5.6	6.0	6.8	7.3	7.4
	4	6.4	7.9	10.0	14.4	16.6

- Phonetic HMMs from 1 to 5 Gaussians/State
- Baum-Welch Reestimation
  - 1 or 4 iterations
- 6 enrollment uterances (1 session)

MLLR Adaptation Results (YOHO)

		Gaussians / State				
		5	10	20	40	80
Regression Classes	1	6.5	6.0	5.9	5.8	5.6
	2	5.3	4.8	4.7	4.6	4.3
	4	9.1	5.6	4.8	4.5	4.2
	8	9.1	5.4	5.1	4.6	4.2
	16	9.1	5.4	4.9	4.7	4.2
	32	9.1	5.4	4.9	4.7	4.2

- Phonetic HMMs with 5,10, 20, 40 y 80 Gauss/state
- MLLR Adaptation
  - 1, 2, 4, 8, 16, 32 regression classes
- 6 enrollment utterances (1 session)