Time-Varying Speaker Recognition

An Introduction

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Speaker recognition

- Voiceprint recognition
- One kind of biometric authentication technology
  - by using speaker-specific information contained in speech waves
  - “non-contact, non-intrusive and easy to use”
  - ranked first by consumer preference among biometric measures according to a Unisys survey

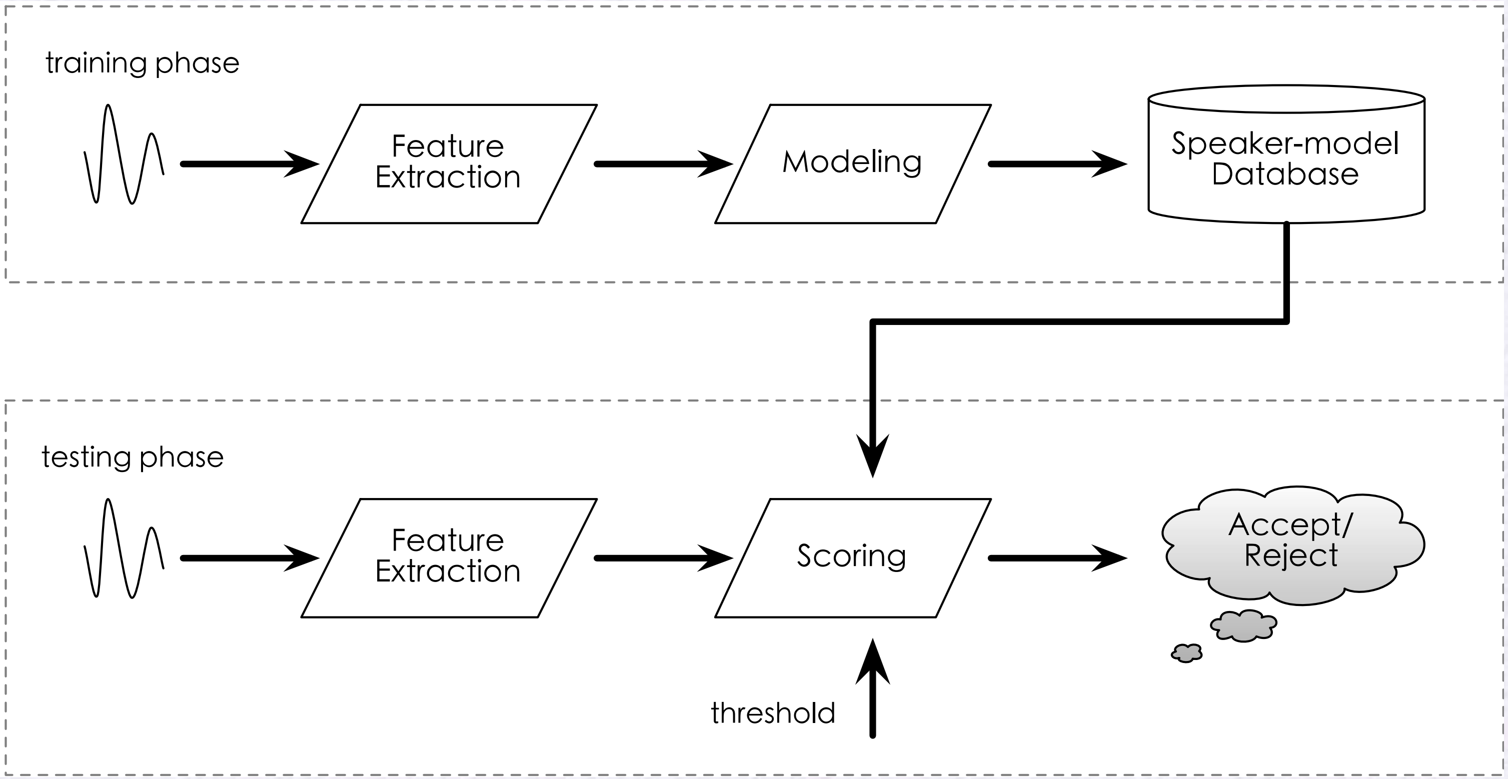
Practical Applications

- Commercial
  - ABN AMRO & Voice Vault
  - NAB & Telstra Salmat VeCommerce
  - CCB & d-Ear
- Public service
  - Wellpoint
- Public & national security

Challenges

- Common ones in speech-related technologies
  - Poor-quality voice samples
  - Background noise
  - Channel mismatch
- Specific ones in speaker recognition technology
  - Short utterance
  - Within-speaker variability
    - Speaking style, emotion, physical status, changes over time…
  - ……

Framework



Framework of a classic speaker verification system

Time-varying Issue

- “Does the voice of an adult change significantly with time? If so, how?” [Kersta 1962]
- “How to deal with long-term variability in people’s voice?” [Furui 1997]
- “Voice changes over time, either in the short-term, the medium-term, or in the long-term.” [Bonastre *et al*. 2003]

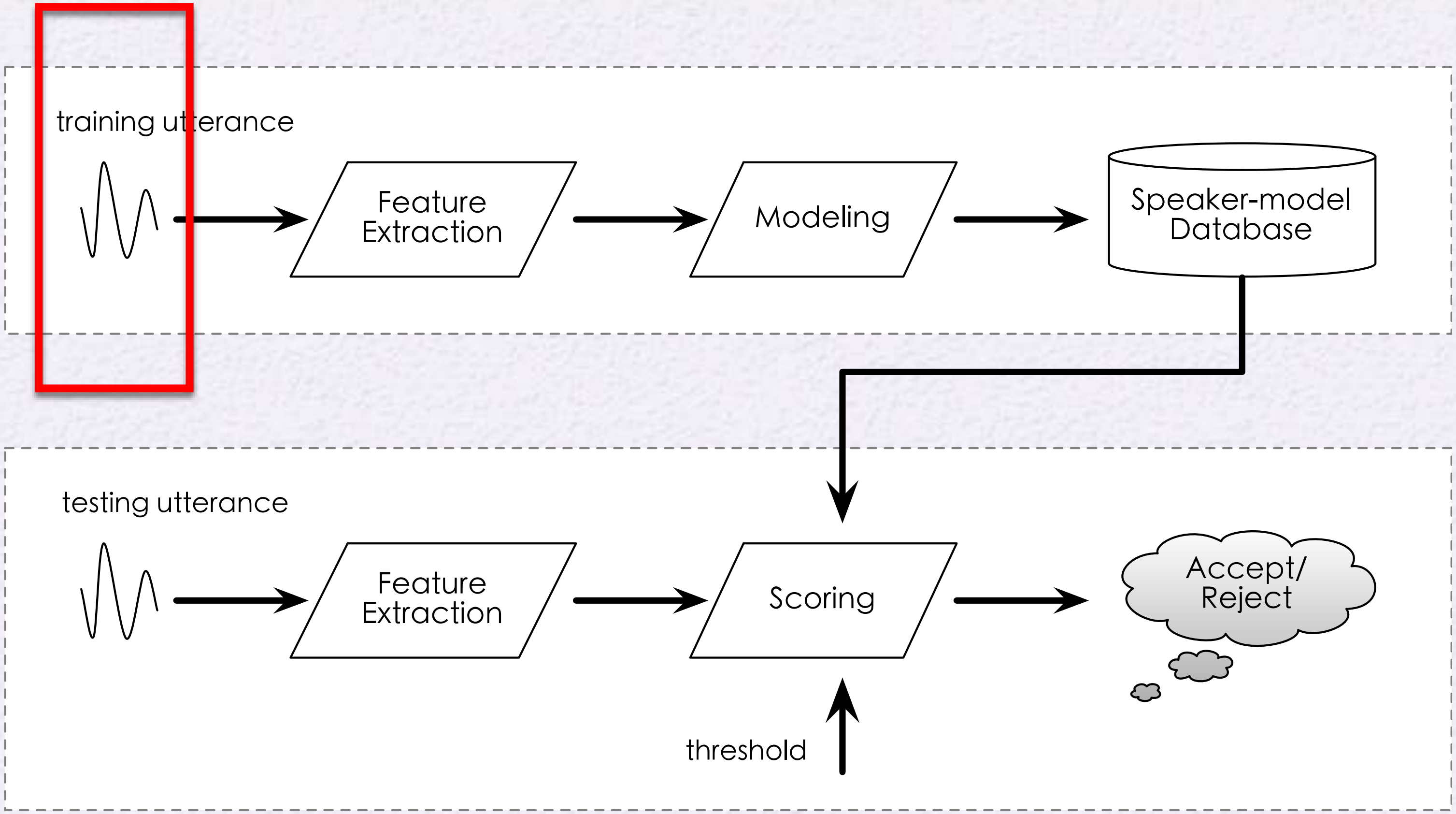
Time-varying Issue

- Performance degradation
  - "The longer the separation between the training and testing recordings, the worse the performance." [Soong *et al.* 1985]
  - A significant loss in accuracy between two sessions separated by 3 months
    - 4~5% in EER [Kato & Shimizu 2003]
    - Ageing was considered to be the cause [Hebert 2008].
  - A voiceprint access control system in CCNT lab
    - 69.02% to 74.19% [Shan & *Yang* 2005]

Time-varying Issue

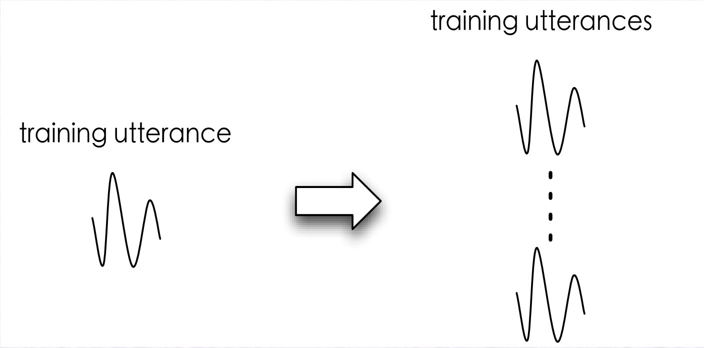
- A generally acknowledged phenomenon
  - Speaker recognition performance degrades with time varying.
  - "Mysterious factors" [Kenny et al. 2007]
- How to deal with this issue?

Methods


training utterance
Feature Extraction
Modeling
Speaker-model Database
testing utterance
Feature Extraction
Scoring
Accept/ Reject
threshold

Structural Training

- More training data lead to more representative models
- Several researchers resorted to several training sessions over a long period of time to help coping with the long-term variability of speech.
  - [Bimbot *et al.* 2004]
  - [Soong *et al.* 1985]



Reference Set

- The best speaker recognition result was obtained when 5 sessions successively separated by at least 1 week were used to define the reference (training) set. [Markel and Davis 1979]

PERCENT OF SPEAKERS CORRECTLY IDENTIFIED AS A FUNCTION OF THE NUMBER OF REFERENCE SESSIONS

SESSIONS			L_V			
NO.	REF.	TEST	30	100	300	1000
2	1-2	3-4	50.36	64.34	71.18	—
2	3-4	1-2	53.45	67.95	75.31	—
3	1-3	4-6	54.29	70.03	79.12	80.58
3	4-6	1-3	57.04	72.69	82.14	89.30
4	1-4	5-8	59.91	76.41	86.73	92.85
4	5-8	1-4	59.26	74.62	83.45	86.34
5	1-5	6-10	61.20	78.65	88.20	93.34
5	6-10	1-5	59.87	75.48	85.27	89.77

Data Augmentation

- When a positive identification of the candidate speaker is made, extra data is appended to the original enrollment data to provide a more universal enrollment model for the candidate.[Beigi 2009] [Beigi

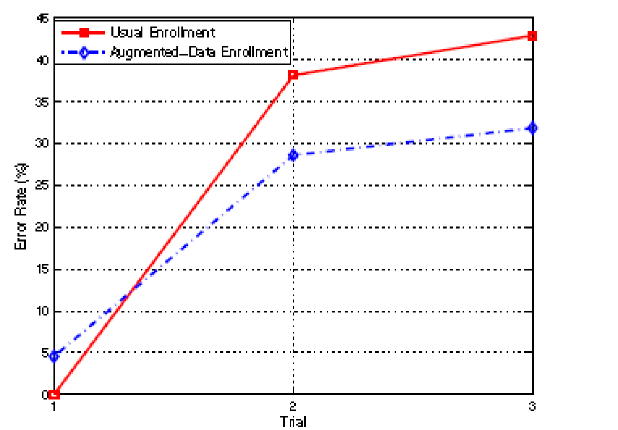
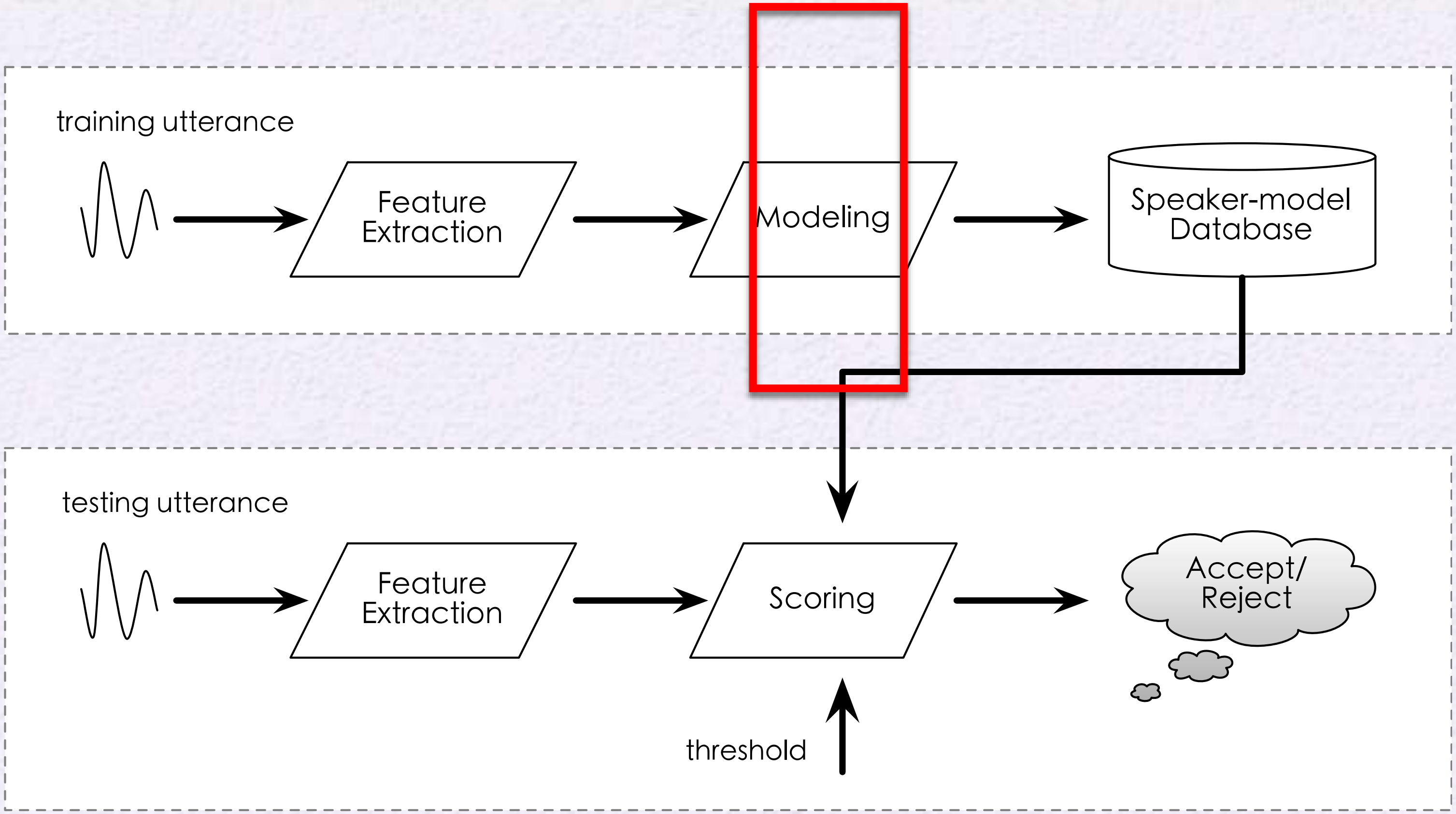


Fig. 3. Identification Time Lapse – Augmented-Data Enrollment

Methods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Model Adaptation

- To use MAP adaptation to adapt from the original model to a new model considering new data at hand. [Beigi 2009] [Beigi 2010]

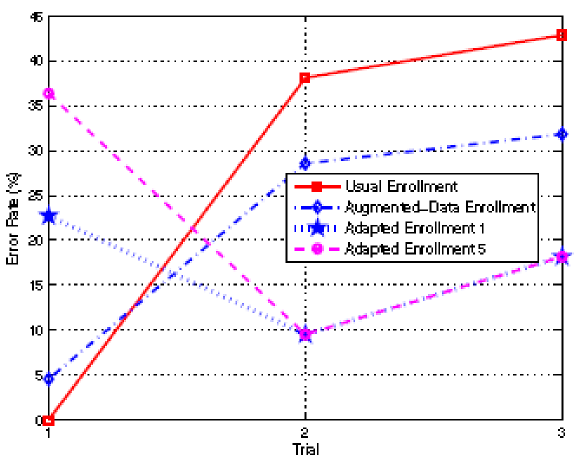
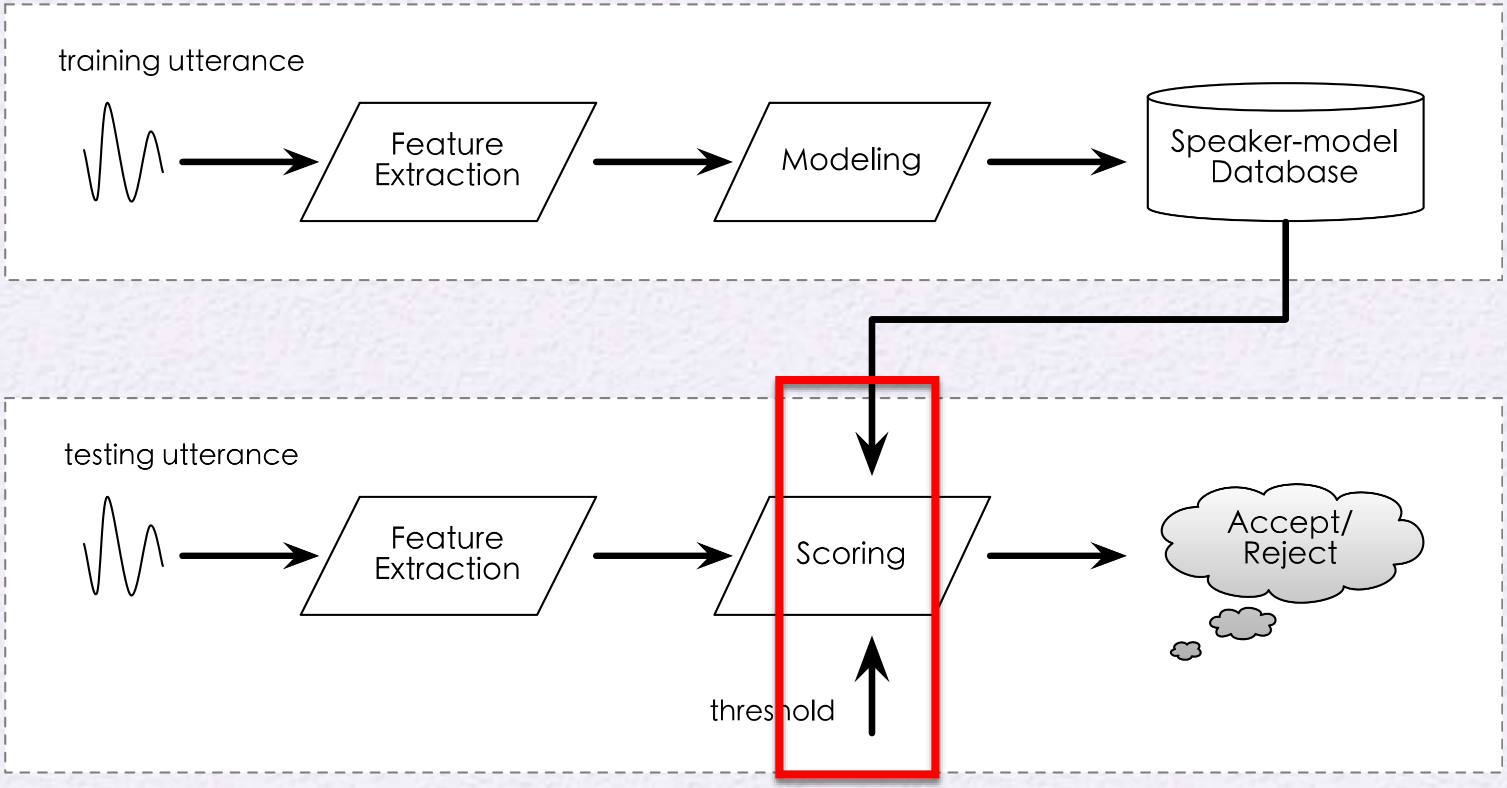


Fig. 5. Identification Time Lapse

Model Adaptation

- To use MLLR-based speaker-adaptation technique to reduce the effects of model aging.
  - [Lamel & Gauvin 2000]
  - EER on the last two sessions is reduced to 1.7% from 2.5%, after adapting the speaker models on data from the intervening session.

Methods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Threshold Decision

- Verification scores of genuine speakers decreased progressively as the time span between training and testing increases, while impostor scores were less affected. [Kelly & Harte 2011] [Kelly *et al.* 2012]

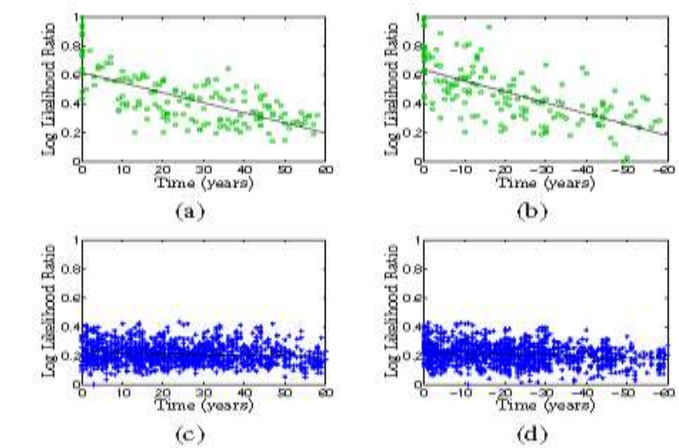


Figure 1. LLR scores for all 18 speakers: (a) genuine speakers, forwards, (b) genuine speakers, backwards, (c) imposters, forwards, (d) imposters, backwards

Threshold Decision

- A stacked classifier method of introducing an ageing-dependent decision boundary was applied, significantly improving long-term verification accuracy. [Kelly & Harte 2011] [Kelly *et al.* 2012]

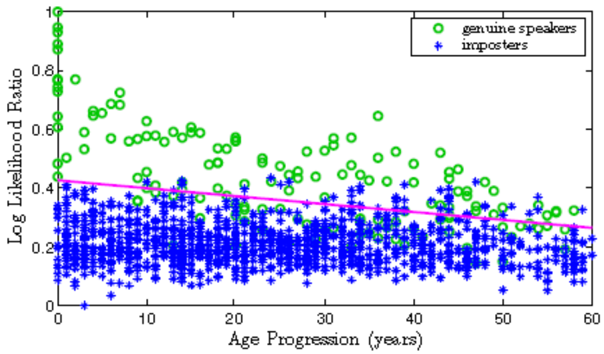
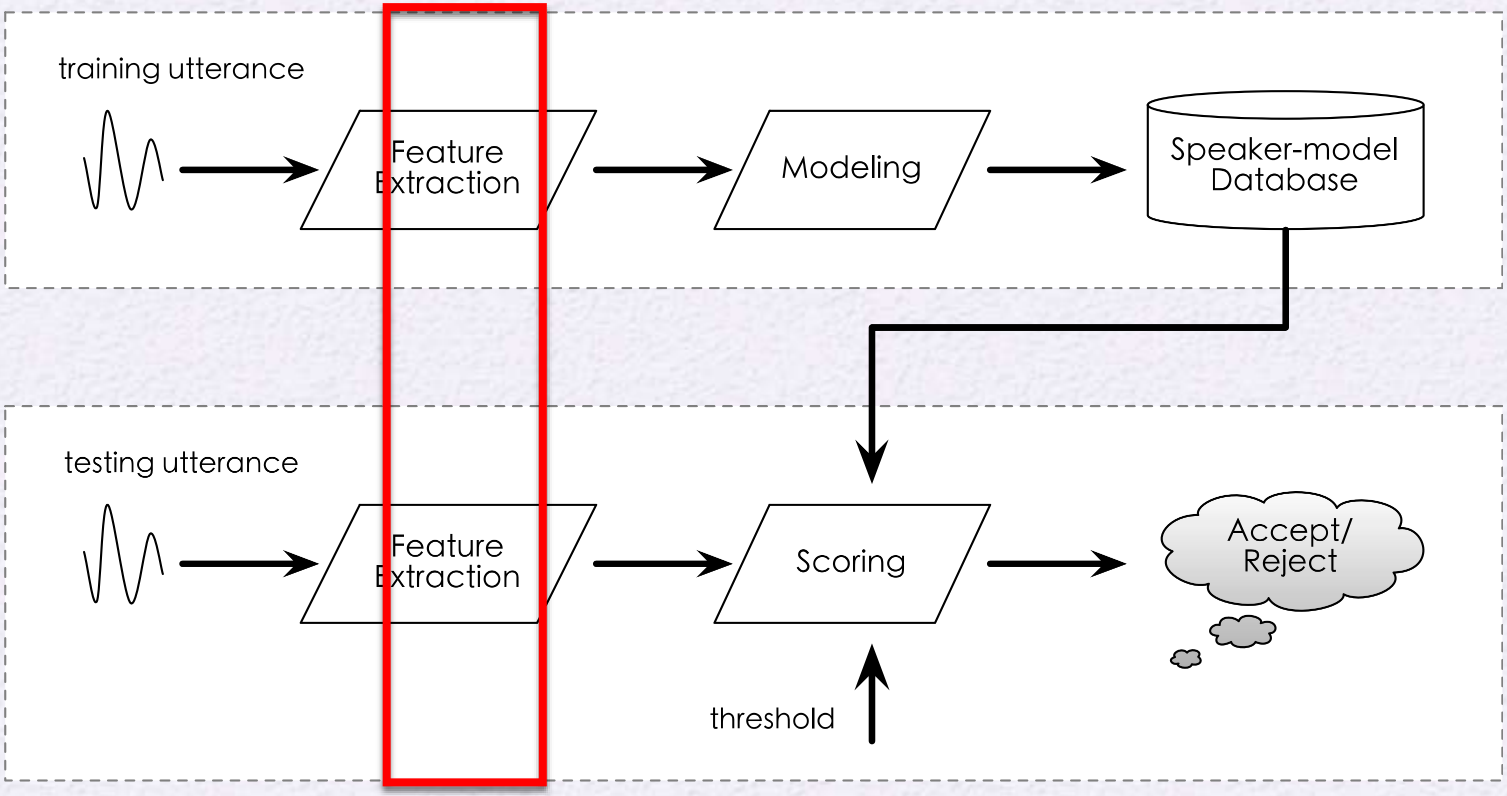


Figure 3. A global ageing-dependent decision boundary trained from 17 speakers' LLR scores and age progression information

Age Progression (years)	5	10	20	40	60
Forwards					
Fixed Threshold	10.8	15.9	26.5	32.2	36.1
Ageing-dependent	7.3	9.2	10.4	17.2	17.5
Backwards					
Fixed Threshold	13.7	18.1	18.9	24.8	29.1
Ageing-dependent	10.2	11.4	12.3	17	21.9

Table 1. Average HTER for all 18 speakers in the Speaker Ageing Database across different ranges of age progression.

Methods



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Feature

- The CORE problem in pattern recognition [Huang *et al.* 2001]
- An IDEAL feature for speaker recognition [Kinnunen & Li 2010] [Rose 2002] [Wolf 1972]
  - Have large between-speaker variability and small within-speaker variability
  - Not be affected by long-term variations in voice

More Stable Features

- Fundamental frequency generally fluctuates randomly across time-varying sessions. [Chen & Yang 2010] [Lu 2008]
- SMFCC [Lu 2008]
  - Smooth the amplitude spectrum and calculate the spectral envelope
  - Gender-dependent performance
    - It works better in female case, and not so good in male case.

An Analysis

- An ideal case
  - Users of speaker recognition systems log-in from time to time, to update their models
  - Advantages
    - Utterances from the genuine speaker
    - "Up-to-date" models
  - Disadvantages
    - User-unfriendly, extra burden

An Analysis

- Structural Training & Model Adaptation
  - More training data and extra adaptation data
  - Advantages
    - No extra burden for users
  - Disadvantages
    - Higher requirements on systems
      - A longer registration process
      - “Threshold” of utterances from the genuine speaker
    - Blind update
      - Nothing to do with the NATURE of time-varying

An Analysis

- Ageing-dependent decision boundary and SMFCC
  - Solutions regarding the trends how fundamental frequency and verification score change over time
  - Disadvantages
    - Both have their own restrictions
  - Advantages
    - This kind of “targeted” attempts should be a natural research direction in time-varying speaker recognition

Data Matters

- Trends are obtained from careful data analysis.
- A proper longitudinal voiceprint database is needed for time-varying research in speaker recognition, which will be elaborated in my second presentation.

References

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Thanks