Exploitation of Phase and Vocal Excitation Modulation Features for Robust Speaker Recognition

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Outline

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1. Introduction
2. Exploration of excitation modulation features
3. Phase information derivation
4. Performance evaluation of modulation features
5. Extraction of robust speaker features
6. Summary

Speaker recognition

- Aim

  Speaker recognition (SR) refers to the process of automatically determining or verifying the identity of a person based on his or her voice.

  Including: Speaker identification (SID), speaker verification (SV).

- Application
  - Sole medium for identity authentication, *e.g.*, telephony banking, ...
  - One modality in multi-modal biometric system, ...

Challenges and difficulties

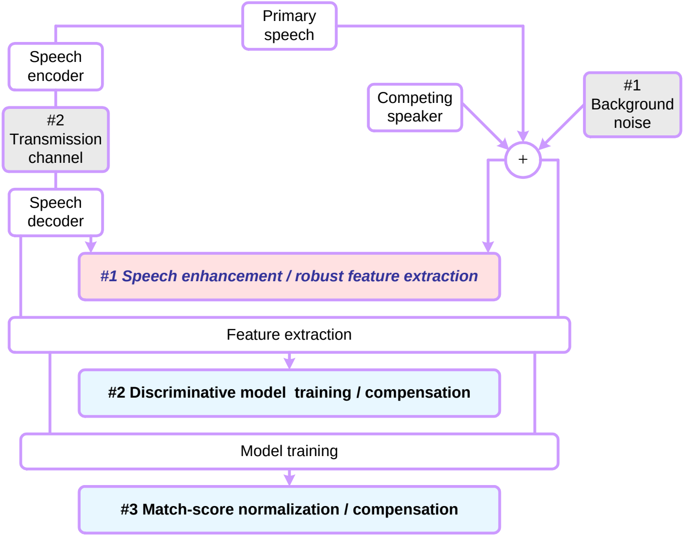
The SR system in practical applications has to handle

- Sparsity of available data set.
- Inconsistence of data quality.
- Variabilities in application scenarios.
  - Background noise.
  - Transmission channels.
  - Emotional, healthy states of speakers.

  ...

...

Robust speaker recognition



Speech feature overview

- Cepstral coefficients
  - Conventional one: Mel-frequency cepstral coefficients (MFCCs).
  - Most commonly used in both speech recognition and speaker recognition systems.
  - Primarily characterize the spectral envelope of a quasi-stationary speech segment.

Speech feature overview

- Exploration of alternative properties
  e.g.,
  - Vocal source (Prasanna, 2006; Zheng, 2007; Gudnason, 2008).
  - Phase information (Ambikairajah, 2007; Grimaldi, 2008).
  - Prosodic characteristics (Atal, 1972; Shriberg, 2005; Adami, 2007).
  - High-level features (Doddington, 2001; Andrews, 2002; Leung, 2006).
- Employment of other parameterization methods
  e.g.,
  - Wavelet transform (Zheng, 2007).
  - Time-frequency principal component analysis (Magrin-Chagnolleau, 2002).
  - Modulation analysis (Dimitriadis, 2005; Thiruvaran, 2008).

Modulation properties in speech

- Formant AM-FM modeling
  - Formant frequency and bandwidth tracking (Potamianos, 1996).
  - Modulation features for robust SR
    - Average log-envelope (Wang, 2003).
    - Dynamic spectral subband centroid (Chen, 2004).
    - Amplitude weighted instantaneous frequency (Dimitriadis, 2005).
    - FM features (Ambikairajah, 2007).
- Sinusoidal representation
  - Pitch tracking (Mcaulay, 1990; Stylianou, 1996).
  - Vocoder (Mcaulay, 1986; Potamianos, 1999).

AM-FM signal modeling

- An AM-FM signal

carrier frequency

arbitrary phase offset

$$x(n) = A(n) \times \cos[\Theta(n)] = A(n) \times \cos\left[\Omega_c n + \Omega_m \sum_{r=1}^{n} q(r) + \phi\right]$$

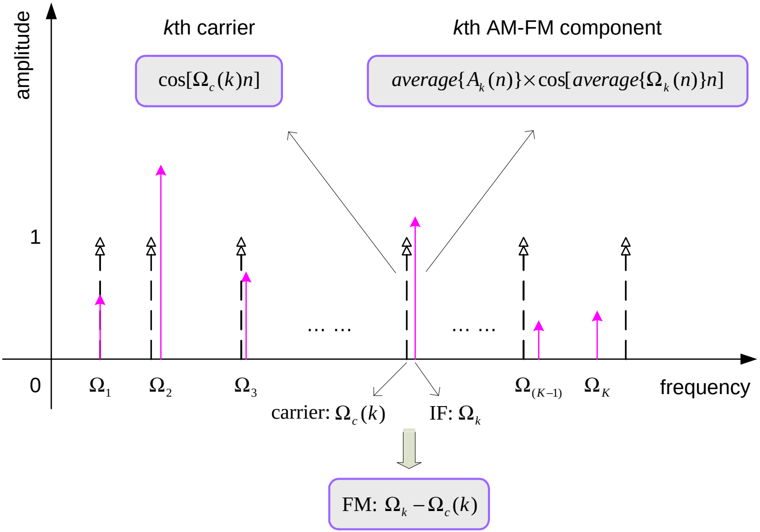
time - varying amplitude

frequency deviation constant

- Time-varying angular frequency:

$$\Omega(n) = \Theta(n) - \Theta(n-1) = \Omega_c + \Omega_m q(n) = \frac{2\pi}{fs} fc + \Omega_m q(n) \longrightarrow \text{FM component}$$

AM-FM signal representation



Motivation of work

- Modulation phenomena in vocal excitation carries speaker-distinctive characteristics.
- Phase related information in speech is important but absent from the magnitude based features.
- Complementary information source helps in improving the performance of MFCCs predominant SR systems.
- Speaker discrimination in practical applications desires robust parameters.

Research focus

- Exploration: how are the speaker-distinctive properties carried by the modulation parameters?
- Investigation: how can we parameterize the modulation parameters into speaker features?
- Evaluation: how complementary are the parameterized features with MFCC features in SR experiments?
- Refinement: how to enhance robustness of modulation features under various application scenarios?

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Excitation signal modeling for SR

For excitation signals,

- spectral analysis mostly concerns pitch-periodicity or harmonic structure properties.
- signal decomposition provides spectro-temporal parameters.
  e.g., in sinusoidal modeling, harmonic plus noise modeling, AM-FM modeling, etc.

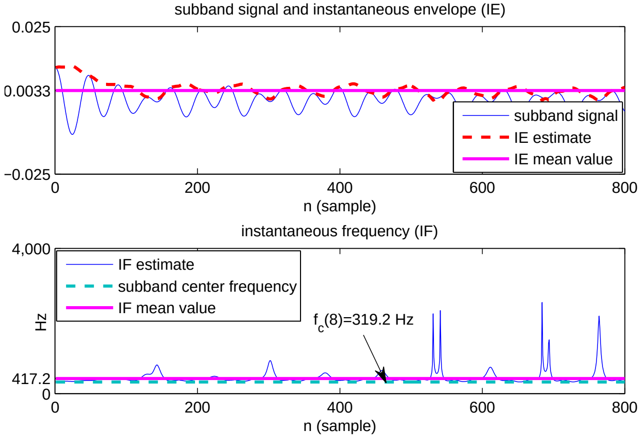
Facilitating extraction of speaker-specific characteristics, we need to

1. select proper source model to use.
2. parameterize model parameters into feature vectors.
3. inspect feature vectors in expressing typical vocal properties.

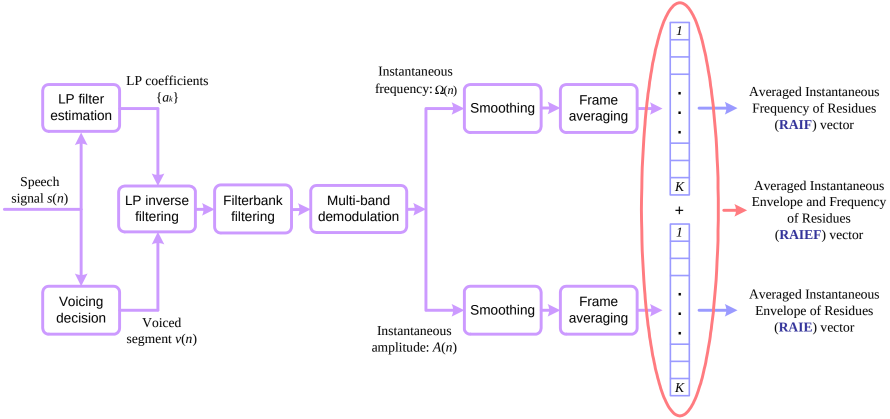
AM-FM excitation representation

Multicomponent AM-FM excitation signal modeling:

- Represents inclusive *monocomponent* signals in terms of time-varying envelope (amplitude) and frequency: $A(n)cos\left[\Theta(n)\right]$.



Excitation modulation feature derivation



- K: Subband number (center frequency in kth subband is $f_c(k)$).
- RAIEF: Combination of RAIE and RAIF vectors.

Excitation modulation features

- Speech production:

  Air flow, vocal fold open and close, vibration activity.

- Vocal excitation properties concerned:
  - Pitch period (F0) and harmonics;
  - Pitch epoch shape;
  - Details embedded between adjacent pitch epochs.

Feature analysis

- Artificially generated pulse trains: $e_1(n)$, $e_2(n)$, $e_3(n)$ and $e_4(n)$.
  - Approximate vocal excitation signals.

	$F0\ (Hz)$	Epoch shape	Details?
$e_1(n)$	86.2	Impulse	No
$e_2(n)$	172.4	Impulse	No
$e_3(n)$	172.4	Triangular pulse	No
$e_4(n)$	172.4	Triangular pulse	Yes

  - F0 values and center frequencies in some bands specially settled.

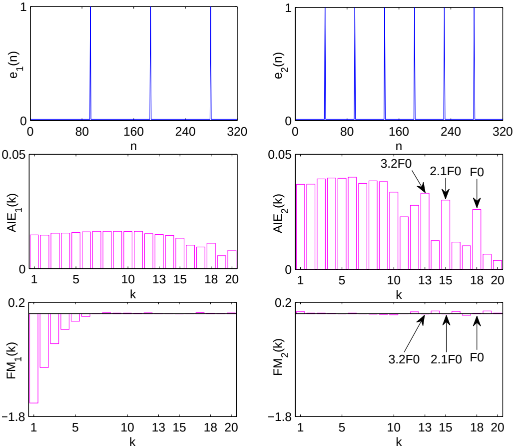
$f_c(18) = F0 = 172.4Hz$	$f_c(15) = 2.1F0$	$f_c(13) = 3.2F0$

Observation 1: pitch variation

AIE and FM for artificial excitation signals with different F0: $e_1(n)$ and $e_2(n)$.

F0: $e_1(n) = 86.2Hz$;

F0: $e_2(n) = 172.4Hz = f_c(18)$.



Observations:

- Amplitude peaks at F0 harmonics.
- Frequency in different bands.

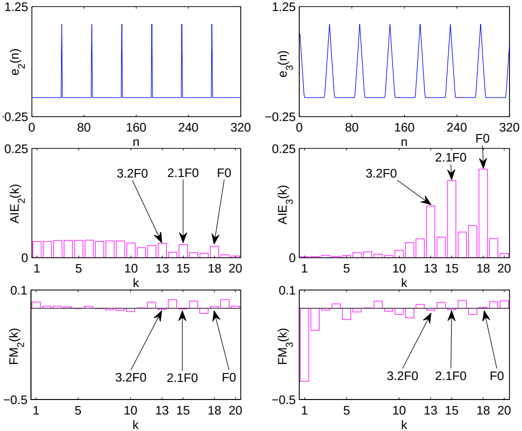
Observation 2: pitch epoch shape

AIE and FM for artificial excitation signals with different epoch shapes: $e_2(n)$ and $e_3(n)$.

Same F0.

Observations:

- Amplitude at F0 harmonics.
- Energy distribution across bands.



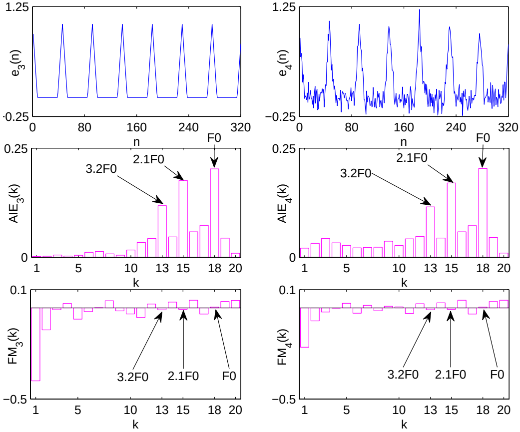
Observation 3: details between epochs

AIE and FM for artificial excitation signals with and without details between adjacent epochs: $e_3(n)$ and $e_4(n)$.

Same F0, same epoch shape.

Observations:

- Amplitude peaks at F0 harmonics.
- Energy in different bands.



Outline

Formant-related modulation properties

- Formant AM-FM modeling
  - Frequency and bandwidth tracking (Potamianos, 1996).
  - FM features (Ambikairajah, 2007).
- A bandlimited signal that describes a formant

$$F_k(n) = A_k(n) exp\left\{ j \left[\Theta_k(n) \right] \right\},$$

is characterized by two sequences:

  - $A_k(n)$ – Amplitude of formant;
  - $\Theta_k(n)$ – Phase of formant.

Primary speech components

A speech signal may contain:

- Formants and pitch harmonics: formulated as mono-component AM-FM terms $A(n)cos[\Theta(n)]$.
- Other components, *e.g.*, transitions between formants, interferences among harmonics and interactions within the vocal tract system, etc.

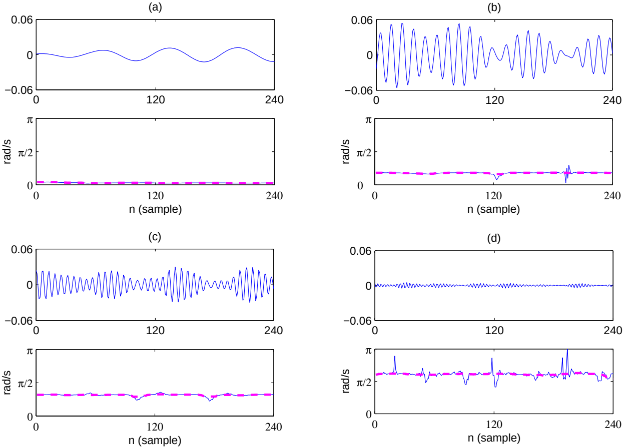
Thus, it can be written as a linear combination of AM-FM components which we called the primary speech components,

$$
\begin{aligned}
s(n) &= \sum_{k=1}^{K} A_k(n)cos\left[\Theta_k(n)\right] + \eta(n) \\
&= \sum_{k=1}^{K} A_k(n)cos\left\{\left[\Omega_c(k)n + \sum_{r=1}^{n} q_k(r)\right]\right\} + \eta(n).
\end{aligned}
$$

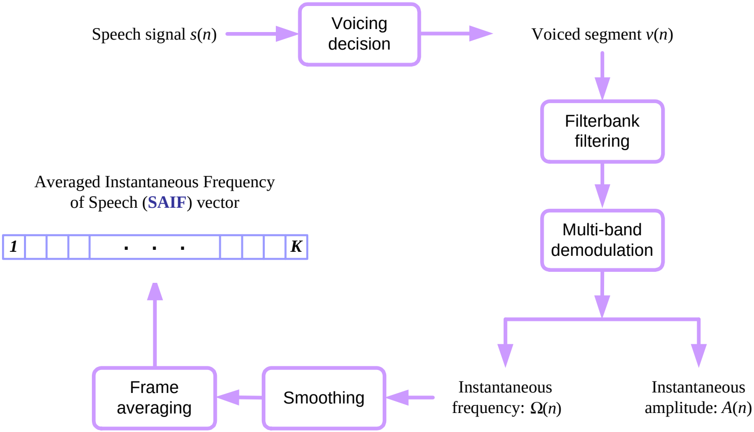
Frequency components in speech

Subband signals and their instantaneous frequency (IF) sequences.

- Centers:
  - (a). 0.03π;
  - (b). 0.18π;
  - (c). 0.31π;
  - (d). 0.61π.



Instantaneous frequency-based features



Feature analysis

- Artificially generated speech sounds: $s_1(n)$ and $s_2(n)$.
  - F0 and formant frequencies are specially settled.

$f_c(36) = 172.4Hz = F0$	$f_c(30) = 2.1F0$	$f_c(26) = 3.2F0$
$f_c(22) = 773.8Hz = F1$	$f_c(17) = 1161.8Hz = F2$	$f_c(7) = 2446.2Hz = F3$

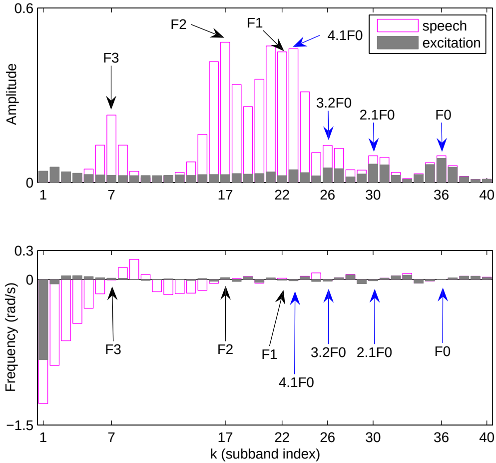
  - Formant bandwidth varies.
    - $s_1(n)$: $10Hz$
    - $s_2(n)$: $200Hz$

Observation 1: formants, harmonics and their interactions

Amplitude and frequency of primary speech components: $s_1(n)$.

Observations:

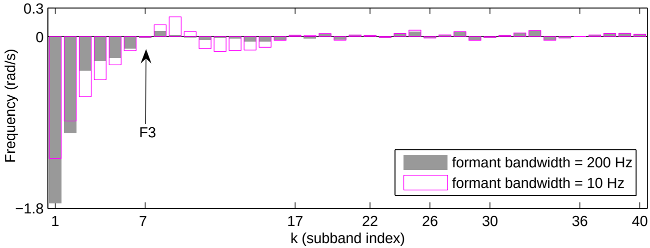
- Amplitude and frequency at formants and F0 harmonics.
- Harmonics noticeable in the lower frequency bands.
- Formants dominant in the higher frequency bands.



Observation 2: Formant bandwidth effect

Frequency of primary speech components: $s_1(n)$ and $s_2(n)$.

- FM around formants:
  - The one assuming larger bandwidth, less peaky formants, produces smaller FM components around the formants.



Outline

Feature evaluation: experimental set-up

- Feature:
  - MFCCs
  - Modulation features: RAIE, RAIF or SAIF
- Database: CU2C (Dual conditional speech corpus, 50 male speakers), NOISEX-92 (Noise database)
- Training data: Microphone speech (CU2C)
- Test data:
  - Matched condition: Microphone speech (CU2C)
  - Mismatched conditions:
    1. Microphone speech (CU2C) + additive noise (NOISEX-92)
    2. Telephone speech (CU2C)
- Modeling: 256 mixtures-GMM
- Score fusion of individual features:

$$\begin{aligned} & score &= \; & w_M \times score_M + w_R \times score_R \quad (w_M + w_R = 1) \\ \text{or} \quad & score &= \; & w_M \times score_M + w_S \times score_S \quad (w_M + w_S = 1) \end{aligned}$$

Evaluation 1: excitation modulation features

Feature configuration		IDER (%)	EER (%)
Baseline	MFCC	2.44	1.52
Effects of feature dimension	RAIE_*20*	40.72	13.17
	RAIF_*20*	35.11	10.42
	RAIE_*40*	27.28	9.46
	RAIF_*40*	19.67	8.01
	RAIEF_*40*	22.50	8.17
Combination with MFCC	MFCC+RAIE_*20*	2.39	1.49
	MFCC+RAIF_*20*	2.28	1.24
	MFCC+RAIE_*40*	2.44	1.44
	MFCC+RAIF_*40*	**2.06**	**1.27**
	MFCC+RAIEF_*40*	2.17	1.36

Evaluation 2: phase-related parameters

Feature configuration		IDER (%)	EER (%)
Baseline	MFCC	2.44	1.52
Effects of feature dimension	SAIF_*20*	6.33	3.72
	SAIF_*40*	**4.78**	**2.70**
Effects of frame length	SAIF_*bil_40*	6.39	3.64
	SAIF_*tril_40*	9.22	4.54
Supplementing cepstral features	MFCC+SAIF_*40*	1.83	1.16
	MFCC+SAIF_*bil_40*	1.89	1.21
	MFCC+SAIF_*tril_40*	1.78	1.33
Combining with source features	RAIE_*40*+SAIF_*40*	5.33	2.69
	RAIF_*40*+SAIF_*40*	4.61	2.65

Analysis 1: on individual features

- MFCCs *vs.* modulation features
  - MFCC features perform much better than the modulation features.
  - The best performed modulation feature has comparable dimension with MFCCs.
- Comparisons among modulation features
  - Dimension: High (40) > Low (20).
  - Configuration: AIF > AIE.
  - Information source: SAIF > RAIF.

Analysis 2: on fusion results

- Recognition accuracy
  - Modulation parameter sets when fusing with MFCCs can produce improved results.
  - Better performed modulation feature + MFCCs produce better fusion results.
- Complementary effects in fusion:

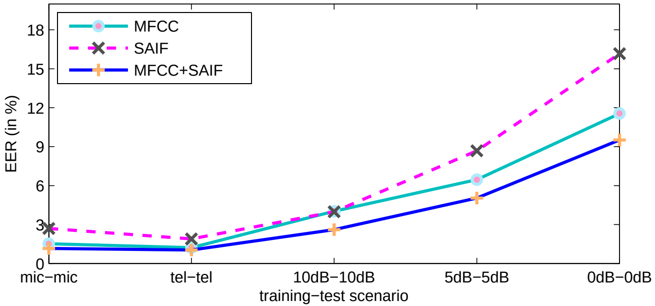
  SAIF + MFCCs > RAIE/RAIF + MFCCs > SAIF + RAIE/RAIF.

Phase information in speech signals can help MFCC-based SR system to achieve higher performance.

Outline

Speaker discrimination under adverse conditions

- Under clean and matched training-test conditions:



- Under mismatched conditions:

Training data	Test data	MFCC	SAIF_*40*	MFCC + SAIF_*40*
Mic.: clean	Mic.: 10dB	17.41	23.47	15.93
Mic.: clean	Tel.	18.94	24.67	18.35

Amplitude-modulated speech components

Dominant frequency of a subband signal relatively stable for a short time interval

Bandwidth, spectral envelop of a subband signal depends on the amplitude

AM – FM component of speech

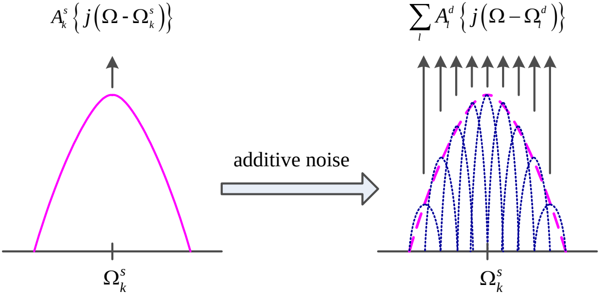
$$A_k^s(n)\cos\left[\Omega_c(k)n+\sum_{r=1}^{n} q_k(r)\right]$$

Take the estimate of dominant frequency, i.e., Ω_k^s, as instantaneous frequency in the concerned subband.

AM component

$$A_k^s(n)\cos\left(\Omega_k^s n\right)$$

Effects of additive noise



- A noise signal contains a large number of narrow-band frequency components.
- Around a specific speech component, *e.g.*, the kth, there are several affecting noise bands exist.

The slowly varying noise components around Ω_k^s generally distort its distribution by moving its mean towards $\Omega_c(k)$ and reducing its variance.

Effects of convolutive noise

In telephone networks, a speech signal $s(n)$ is transmitted through a channel with impulse response $c(n)$.

For the kth subband:

Assumption: $c_k(n) \quad = \quad A_k^c \delta(n - n_k^c)$

Output signal:

$$
\begin{aligned}
z_k(n) &= s_k(n) \otimes c_k(n) \\
&= \left\{ A_k^s(n) cos(\Omega_k^s n) \right\} \otimes \left\{ A_k^c \delta(n - n_k^c) \right\} \\
&= \underbrace{\left\{ A_k^c A_k^s(n - n_k^c) \right\}}_{\text{Amplitude}} \cdot \underbrace{\left\{ cos(\Omega_k^s n - \Omega_k^s n_k^c) \right\}}_{\text{Phase}}
\end{aligned}
$$

Brief introduction to feature mapping

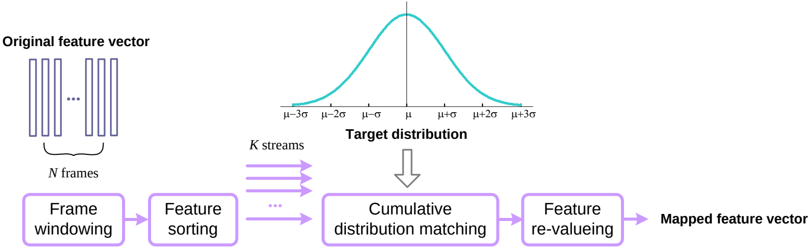
Feature mapping for speaker verification

- Proposed by Jason Pelecanos and Sridha Sridharan ("Feature Warping for Robust Speaker Verification", *2001: A Speaker Odyssey*).
- A post-processing method for robust feature extraction.
- Requires no noise statistics or channel models.

It is found that feature mapping method works well for cepstral features.

Then, what is a proper mapping process for phase-related parameters?

Mechanism of feature mapping



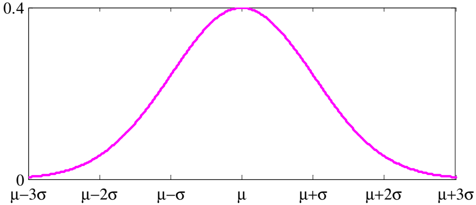
- **Frame windowing**: a sliding window to isolate N frames of speech features.
- **Feature sorting**: feature values in each stream sorted descendingly assuming rank 1 to N.
- **Cumulative distribution matching**: find the *relative* position for the feature in the target distribution

$$\int_1^u f_m(x)dx = \int_1^v f_t(y)dy,$$

u, v: ranks of the current feature in the measured and target distributions.

- **Feature re-valuing**: find the *absolute* feature value of the mapped parameter.

Feature-specific target distributions



MFCCs:

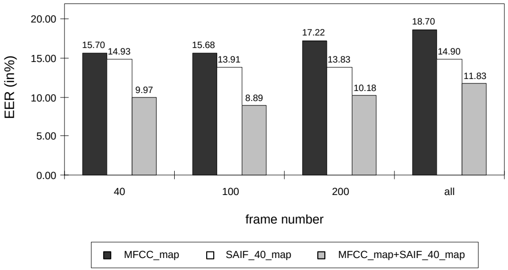
- Measured distribution: multi-modal in nature.
- All feature streams share the same target distribution: $N(0,1)$.

SAIF: *Histograms*

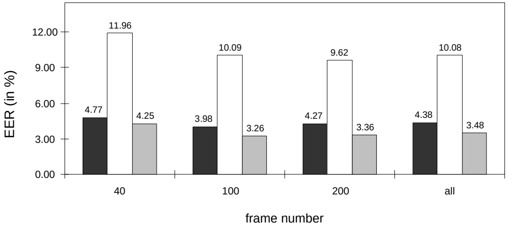
- Measured distribution: uni-modal.
- Individual target for each feature stream: $N(\mu, \sigma^2)$. For the kth parameter:
  - μ: $\Omega_c(k)$
  - σ: bandwidth $(ERB(k))/6$

Experimental results

(a). mismatched noise condition



(b). mismatched channel condition



Benchmark results:

	MFCC	SAIF_*40*	MFCC+SAIF_*40*
(a)	17.41	23.47	15.93
(b)	18.94	24.67	18.35

- Two mismatched conditions: noise or channel mismatch.
- Four kinds of window size for feature mapping:
  - 40 frame: 0.4s
  - 100 frame: 1s
  - 200 frame: 2s
  - all frame: length of the utterance

Observations and analysis

- Recognition performance
  - Performance of individual MFCC and SAIF features improved.
  - Combination of the magnitude-based and phase-related parameters demonstrate advantages.
- Feature mapping effectiveness
  - Under channel mismatch condition, feature mapping leads to larger improvement, especially for MFCCs.
  - For additive noise condition, SAIF features get more benefit from the mapping.

Outline

Summary

- Speaker-specific characteristics are identified in primary amplitude and frequency components of decomposed speech signal.
- Modulation feature vectors are generated by extracting the most dominant components in multi-band time-varying modulation parameters.
- Complementary assistance of phase and vocal excitation modulation features to MFCCs are confirmed by improvements of SR performance.
- Robustness of speaker parameters in various scenarios are enhanced by feature-dependent mapping approach.

Future directions

For robust speaker recognition,

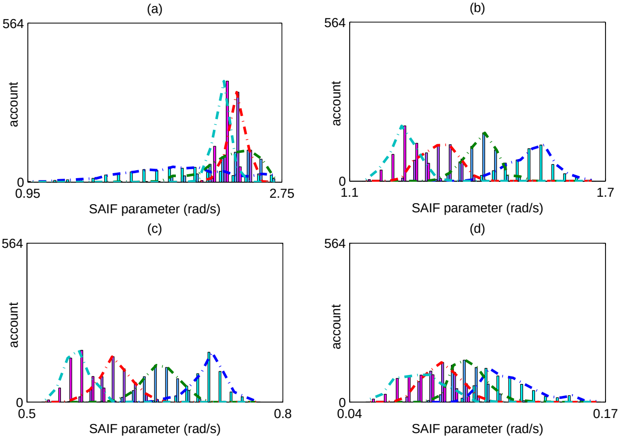
- Producing flexible forms for higher efficient features.
  e.g., weighting scheme among streams in a vector, selection criterion.
- Generating features from unvoiced segments.

For others,

- Modeling source signal of speech.
- Learning to recognize/predict human emotional states.
  - Application scenarios: human-computer interaction (HCI), interactive learning system, intelligent robotics, emotional state monitoring, etc.
  - Fusion with other modalities: video, EEG & physiological signals, etc.

Thank you very much!

Histogram statistics of SAIF streams

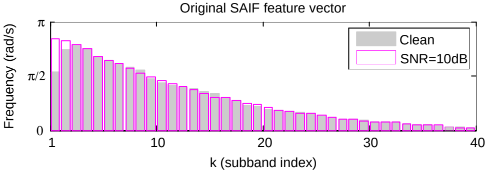


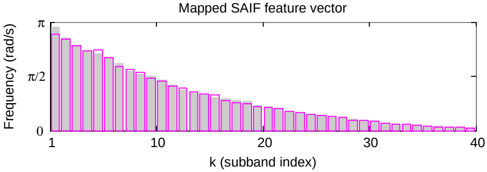
(a). $k = 1, \ldots, 4$, (b). $k = 10, \ldots, 13$, (c). $k = 20, \ldots, 23$, and (d). $k = 37, \ldots, 40$.

Target distribution

Original *vs.* mapped parameters

SAIF feature vectors:





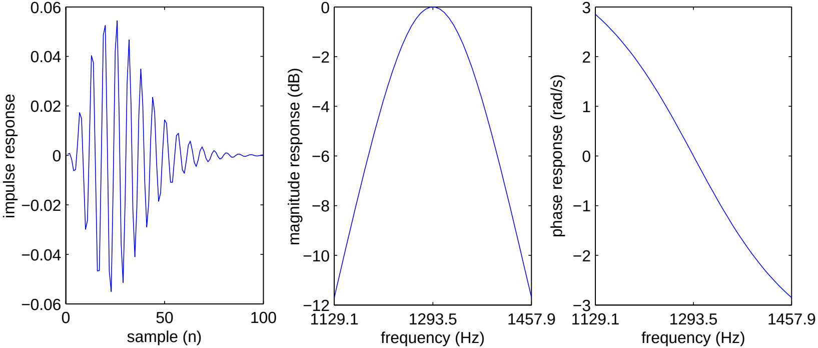
Observations:

- Before mapping:
  Difference is obvious in the high frequency region.

- After mapping:
  Difference in the high frequency region is mitigated, while they are small among other regions.

Gammatone filter-bank

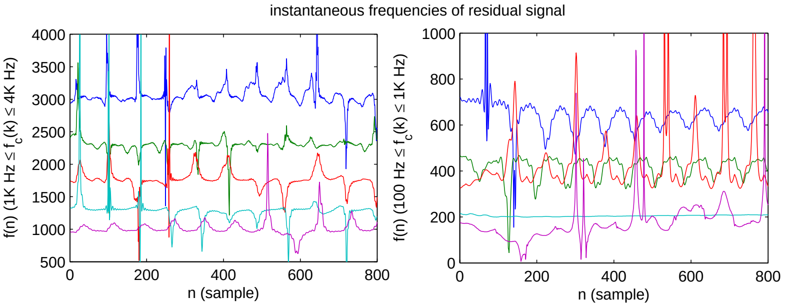
- Model the cochlea by a bank of overlapping bandpass filter.
- Filters are evenly-distributed on an ERB scale.
- The 4th filter among the 10: $f_c(4) = 1293.5Hz$, $bw(4) = 164.4Hz$.



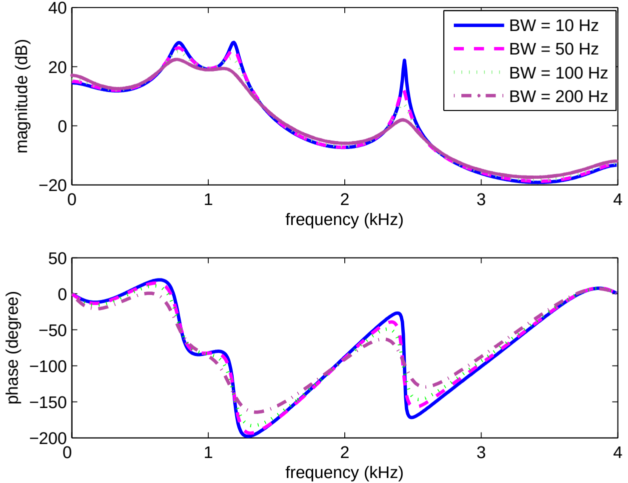
IF in excitation signal

Table: Center frequencies and ERB bandwidths of a 10-channeled Gamma-tone filter bank spaced on [100Hz, 4k Hz] (in Hz).

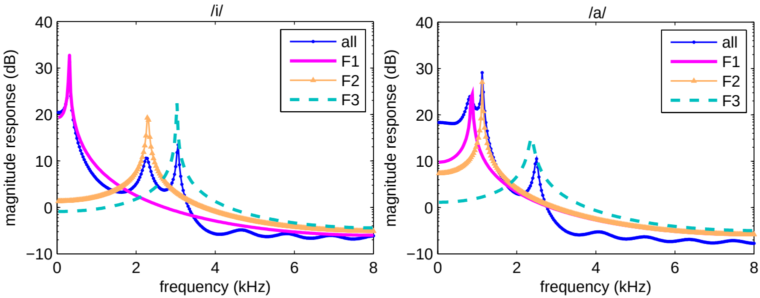
k	1	2	3	4	5	6	7	8	9	10
$f_c(k)$	3046.8	2308.5	1736.5	1293.5	950.4	684.6	478.7	319.2	195.7	100
$ERB(k)$	353.8	274.0	212.2	164.4	127.3	98.6	76.4	59.2	45.8	35.5



Formant bandwidth effect: LP spectra



Vocal tract resonance



The complex conjugate poles correspond to a vocal tract resonance is

$$z_k, z_k^* = exp\big(-\frac{\sigma_k}{f_s}\big)exp\big(\pm j\frac{2\pi}{f_s}F_k\big).$$

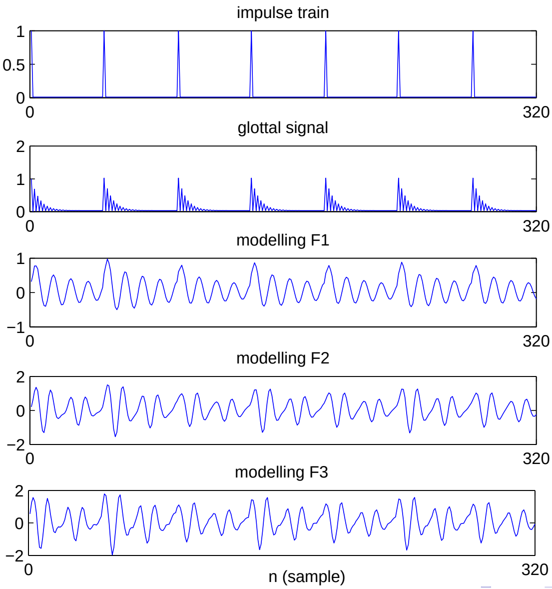
In the z transform domain, the bandwidth is determined by the radius of the poles, i.e.,

$$r_k = |z_k| = exp\big(-\frac{\sigma_k}{f_s}\big),$$

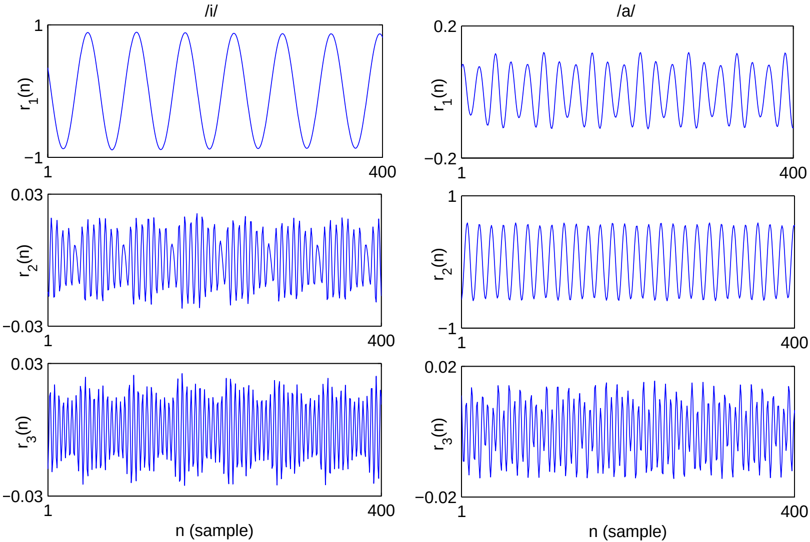
while, the angles of the conjugate poles from the origin are

$$\theta_k = \pm\frac{2\pi}{f_s}F_k.$$

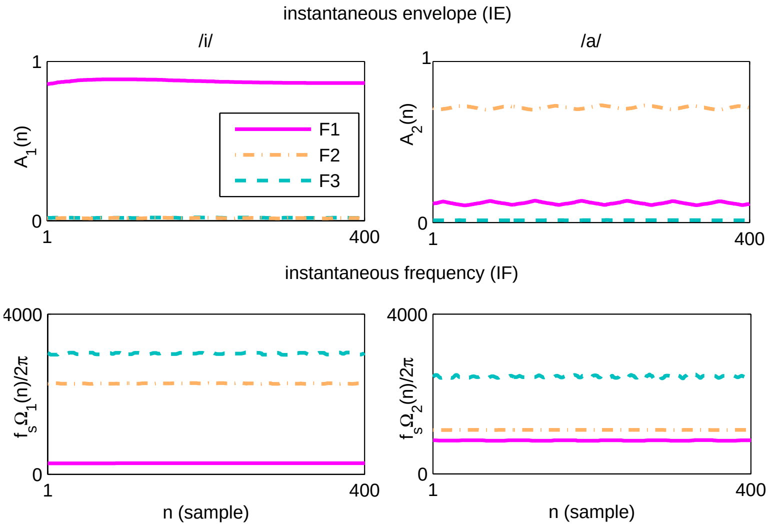
Voiced sound synthesis



Waveform of resonant signals



Instantaneous envelope and frequency of resonant signals



SID & SV tests

- SID tests
  - Close-set.
  - 1800 tests for each speaker.
- SV tests
  - 36 claimant tests.
  - 1764 imposter tests for each speaker.