MULTIPLE HYPOTHESIS TRACKING FOR OVERLAPPING SPEAKER SEGMENTATION

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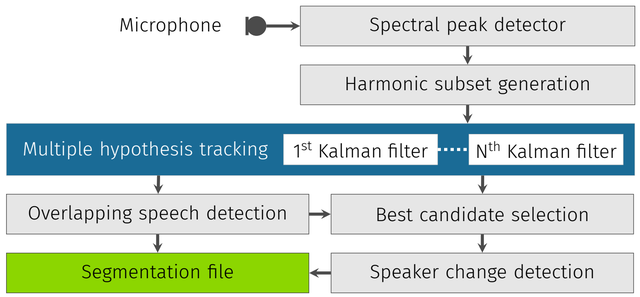
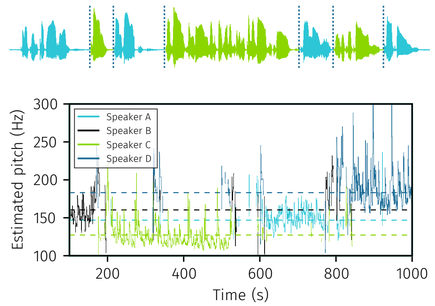
1. Overview & Proposed system

- **What does this paper propose?**
  A multiple hypothesis tracking (MHT) method that exploits the harmonic structure associated with the pitch in voiced speech in order to segment the onsets of speech from multiple, overlapping speakers.
- **How well does this proposed method perform?**
  Comparable segmentation performance can be achieved for overlapping speech when evaluated against a deep learning approach which requires labelled training data.



2. Motivation

- **What is speaker diarization?**
  Answers the question "who spoke when?" and is required for applications, such as speaker indexing and automatic speech recognition (ASR).
- **Is performing segmentation before clustering really that useful?**
  If correct segmentation is performed before clustering then each segment will contain the maximum amount of information possible on the speaker's identity.
- **Why use pitch for segmentation?**
  A study [1] of meetings in the AMI corpus has shown that a pitch change is a strong indicator of a speaker change.



3. Harmonic subset generation

Example for a given frame

Peak detection: $\Phi_t = \{100,\ 200,\ 350,\ \ 400,\ \ 450\}$
Reliability: $\Psi_t = \{630,\ 450,\ 49.0,\ 23.0,\ 0.82\}$

Remove unreliable peak detection (reliability > 10)
Reliable peak detections: $\hat{\Phi}_t = \{100, 200, 350, 400\}$

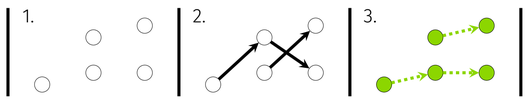
Possible observations from peak detections:
$\boldsymbol{z}_{t,0} = \{100, 200, 400\}$ or $\boldsymbol{z}_{t,1} = \{200, 400\}$

Ψ_t	Φ_t	$\hat{\Phi}_t$	$\boldsymbol{z}_{t,0}$	$\boldsymbol{z}_{t,1}$
0.82, 450 Hz	×			
23.0, 400 Hz	×		× F_3 ×	F_1 ×
49.0, 350 Hz	×		×	
450, 200 Hz	×		× F_1 ×	F_0 ×
630, 100 Hz	×		× F_0 ×	

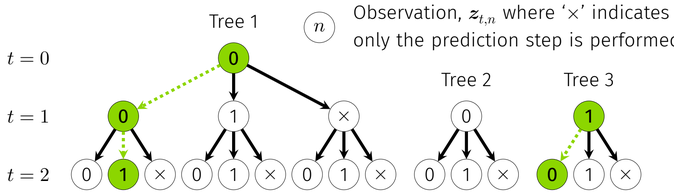
4. Multiple hypothesis tracking

Tracking observations

1. Observations in time
2. Possible track
3. Best track



Multiple hypothesis tracking

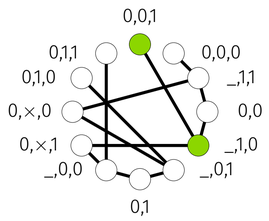


n Observation, $\boldsymbol{z}_{t,n}$ where '×' indicates that only the prediction step is performed.

Maximum weighted clique (MWC)

Used to find the most likely set of tracks which do not conflict.

Each node is a track hypothesis and each edge connects 2 tracks which do not conflict. A score is assigned which is calculated by taking the average value of all previous estimation errors.



5. Kalman filter for pitch tracking

The state equation for the i^{th} speaker:

$$x_{i,t} = x_{i,t-1} + w_{i,t}, \quad w_{i,t} \in \mathcal{N}(0, \sigma_w^2),$$

with observation:

$$\boldsymbol{z}_{t,n} = \boldsymbol{h}_{t,n} x_t + \boldsymbol{v}_t,$$
$$\boldsymbol{v}_t \in \mathcal{N}(0, \boldsymbol{R}), \quad \boldsymbol{R} = \begin{bmatrix} \sigma_v^2 & & \\ & \ddots & \\ & & \sigma_v^2 \end{bmatrix}.$$

Prediction step:

$$\hat{x}_{i,t|t-1} = \hat{x}_{i,t-1|t-1}, \quad p_{i,t|t-1} = p_{i,t-1|t-1} + \sigma_w^2.$$

Update step:

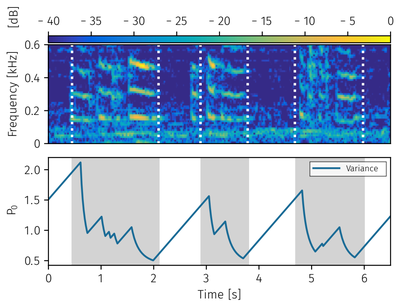
$$\hat{x}_{i,t|t} = \hat{x}_{i,t|t-1} + \boldsymbol{k}_{i,t}^T (\boldsymbol{z}_{t,n} - \boldsymbol{h}_{t,n} \hat{x}_{i,t|t-1}), \quad p_{i,t|t} = (1 - \boldsymbol{k}_{i,t}^T \boldsymbol{h}_{t,n})^2 p_{i,t|t-1} + \boldsymbol{k}_{i,t}^T \boldsymbol{R} \boldsymbol{k}_{i,t}.$$

Optimal Kalman gain:

$$\boldsymbol{k}_{i,t}^T = p_{i,t|t-1} \boldsymbol{h}_{t,n}^T \boldsymbol{S}_{i,t}^{-1}, \quad \boldsymbol{S}_{i,t} = \boldsymbol{h}_{t,n} p_{i,t|t-1} \boldsymbol{h}_{t,n}^T + \boldsymbol{R}.$$

Estimation error:

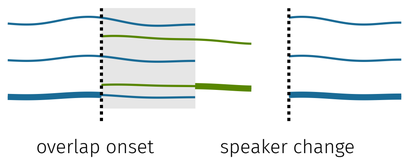
$$\boldsymbol{y}_{i,t|t} = \boldsymbol{z}_{t,n} - \boldsymbol{h}_{t,n} \hat{x}_{i,t|t}.$$



6. Speaker segmentation

Overlapping speech detection

An overlap is detected when there are multiple tracks that are not harmonically related (grey box).



Speaker change detection

Overlaps are removed and the best F_0 candidate (bold) is selected out of the remaining tracks. [1] is used to detect speaker changes.

Segmentation file

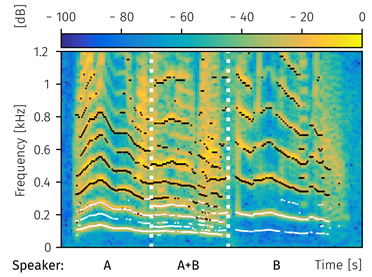
The union of 'overlap onsets' and 'speaker changes'.

[1] A. Hogg *et al*, "Speaker change detection using fundamental frequency with application to multi-talker segmentation," in *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*

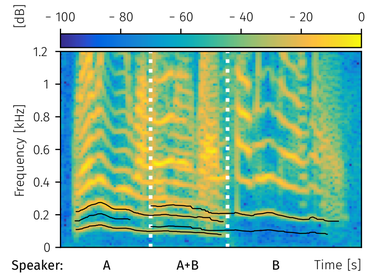
7. Results

Illustrative (TIMIT) example

Two speech segments from the TIMIT corpus were selected and partially overlapped.



Observations where the white crosses denote F_0



Tracks generated from observations

Evaluation on AMI corpus

Baseline: bidirectional long short term memory networks (BLSTM) method [2] where the model was trained on AMI employing MFCC, their first and second derivatives, as well as the first and second derivatives of the energy.

Method	Hit	Miss	MSE	Multi-Hit	FA
Baseline	75.0%	25.0%	0.0115	16.7%	30.8%
Proposed	78.6%	21.4%	0.0067	42.9%	35.3%

Input: Individual headset microphone (IHM) mixed-down stream

Method	Hit	Miss	MSE	Multi-Hit	FA
Baseline	70.0%	30.0%	0.0077	20.0%	53.9%
Proposed	78.6%	21.4%	0.0237	64.3%	55.5%

Input: Single distance microphone (SDM) stream

[2] R. Yin *et al*, "Speaker change detection in broadcast tv using bidirectional long short-term memory networks," in *2017 Annual Conference of the International Speech Communication Association (INTERSPEECH)*

8. Conclusion

- Presents a novel segmentation system that utilises a MHT framework to track multiple speakers even when they are talking simultaneously.
- Shows that by exploiting the harmonic structure of voiced speech, it is possible to detect when more than one speaker is active in a speech signal.
- Shows that the newly proposed system achieves comparable segmentation performance when it is compared against a recent machine learning method.