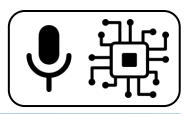
Computational Analysis of Sound and Music



Environmental Sound Analysis – Sound Event Detection 1

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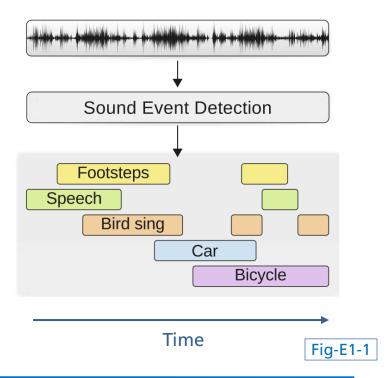
Outline

- Introduction
- Challenges & Related Tasks
- Pipeline
- Evaluation



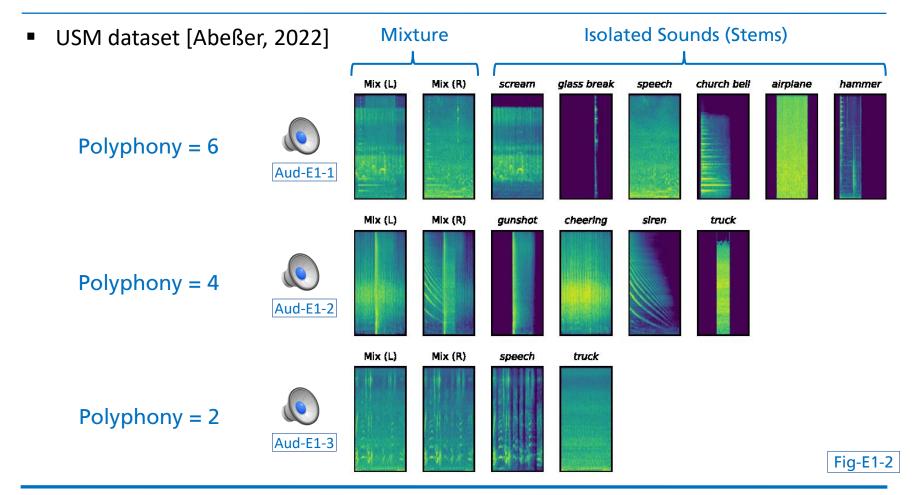
Introduction

- Sound event detection → 2 simultaneous tasks
 - Segmentation (detection of temporal boundaries)
 - Classification (type of sound)
- Sound polyphony
 - Number of simultaneous sounds
 - Depends on the acoustic scene composition & sound sources





Introduction

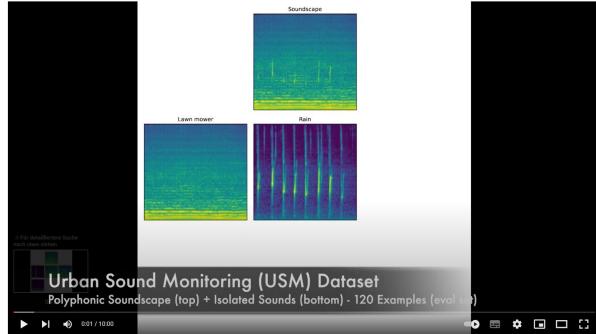




Introduction

Demo-Video

USM dataset [Abeßer, 2022]



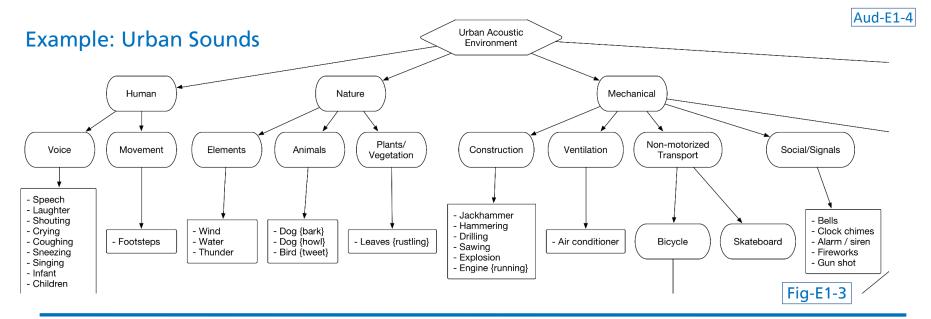
Demo of the Urban Sound Monitoring (USM) Dataset for Polyphonic Sound Event Tagging



Introduction

- Sound source categories
 - Humans, animals, vehicles, tools, machines, climate, ...
- Sound hierarchies
 - Based on regional origin & sound characteristics

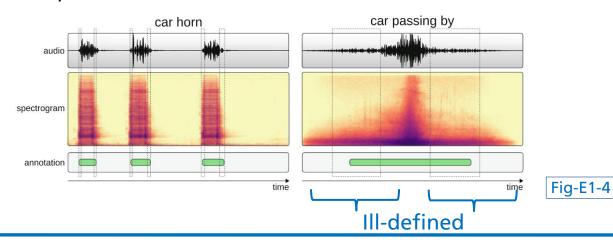






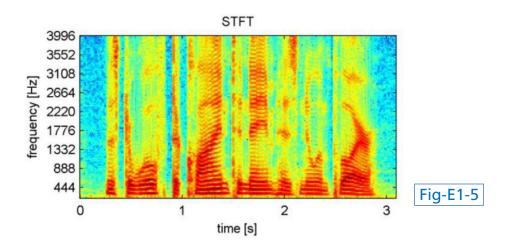
Challenges

- Sound characteristics
 - Short transients, noise-like signals, harmonic / inharmonic signals
- Sound durations
 - Short (gun shot, door knock) → long / stationary (machines, wind)
- Ill-defined temporal boundaries
 - Complicates annotation & detection



Challenges

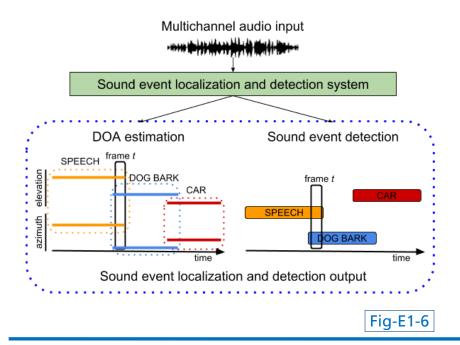
- Sound appear in the foreground & background
 - depending on relative sound source position
- Non-local / sparse energy distribution
 - Example: fundamental frequency & overtones

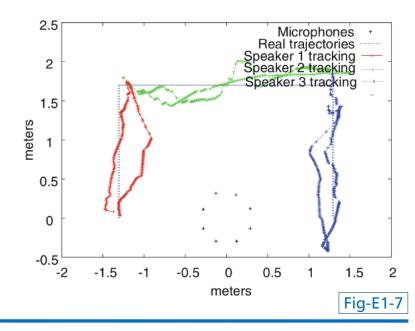




Related Tasks

- Sound event localization & tracking
 - Multichannel audio recordings (e.g., first-order ambisonic microphones)
- Estimate direction-of-arrival (DOA) & track source movement

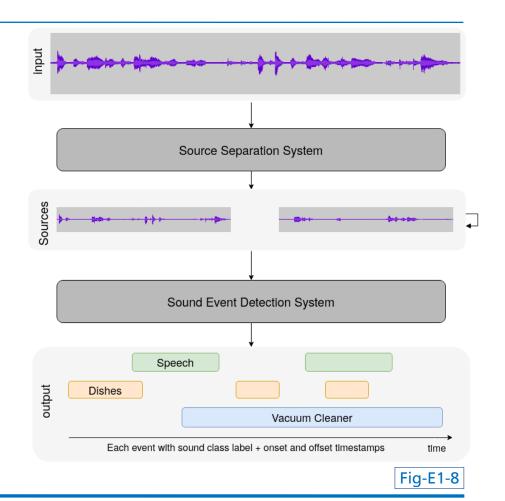






Related Tasks

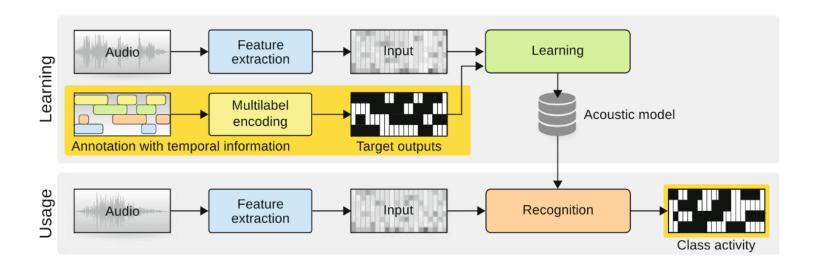
- Source separation
 - Facilitates sound event detection (fewer background sounds)
- Chicken-egg problem
 - Alternative: soundinformed sourceseparation





Pipeline

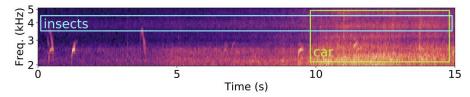
- Supervised learning pipeline
 - Feature extraction & pre-processing
 - Label encoding
 - Acoustic modeling



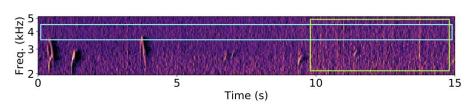


Pipeline

- Feature extraction
 - 1D features (audio samples) → "end-to-end learning"
 - 2D features (mel-spectrogram, STFT)
- Feature pre-processing
 - Log-magnitude scaling
 - Per-channel energy (PCEN) [Lostanlen, 2019]
 - Dynamic range compression
 - Adaptive gain control
 - Suppresses stationary (background) noise



(a) Logarithmic transformation.

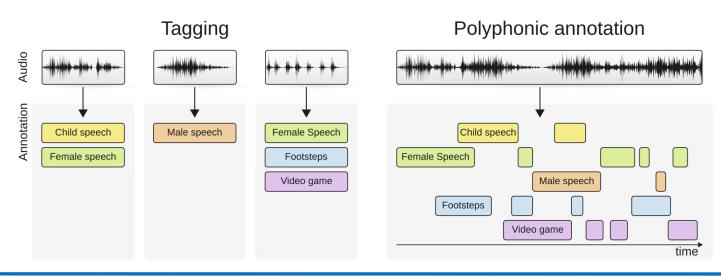


(b) Per-channel energy normalization (PCEN).



Pipeline

- Annotation
 - Quality of "ground truth"? (limited agreement / reliability)
 - Different granularities
 - Tagging / Global level ("weak" labels) → cheap
 - Event-level ("strong" labels) → expensive

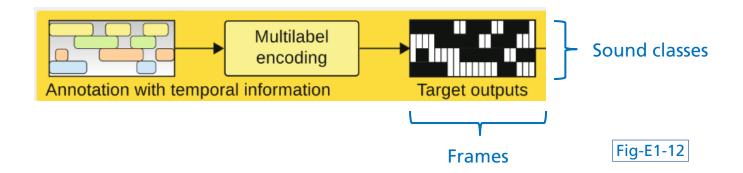


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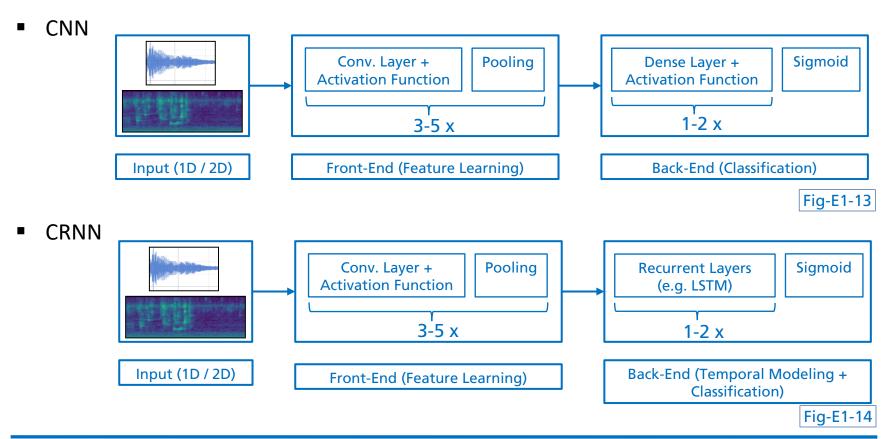
Pipeline

- Label encoding
 - Binarized sound activity (0/1)
 - Multilabel classification
 - 1 (independent) binary detector per class
 - Temporal resolution (duration of each annotated time frame)



Pipeline

Typical neural network architectures



Evaluation

- Evaluate SED → binary classification results on a frame-level
- Compare reference with predictions
- Count TP/FN/FP → aggregate over time → compute metrics

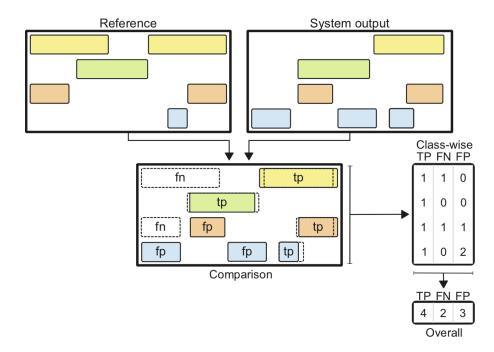
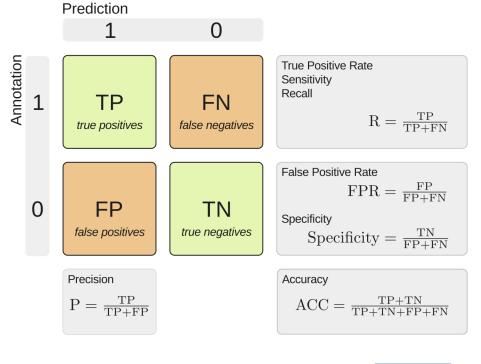


Fig-E1-15



Evaluation

- Binary classification evaluation
 - True/false positives (TP/FP)
 - True/false negatives (TN/FN)
- Metrics
 - Precision
 - Recall
 - Accuracy
 - F-score





Programming session



Fig-A2-13

References

Images

```
Fig-E1-1: [Virtanen, 2018], p. 15, Fig. 2.1
Fig-E1-2: [Own]
Fig-E1-3: https://urbansounddataset.weebly.com/uploads/4/3/9/4/4394963/3427002 orig.png
Fig-E1-4: [Virtanen, 2018], p. 157, Fig. 6.3
Fig-E1-5: https://towardsdatascience.com/whats-wrong-with-spectrograms-and-cnns-for-audio-processing-311377d7ccd
Fig-E1-6: http://dcase.community/challenge2019/task-sound-event-localization-and-detection, Fig. 1
Fig-E1-7: [Virtanen, 2018], p. 267, Fig. 9.7
Fig-E1-8: http://dcase.community/challenge2020/task-sound-event-detection-and-separation-in-domestic-environments, Fig. 2
Fig-E1-9: [Virtanen, 2018], p. 31, Fig. 2.11
Fig-E1-10: [Lostanlen, 2019], p. 1, Fig. 1
Fig-E1-11: [Virtanen, 2018], p. 154, Fig. 6.2
Fig-E1-12: [Virtanen, 2018], p. 31, Fig. 2.11 (excerpt)
Fig-E1-13 & 14: [Own]
Fig-E1-15: [Virtanen, 2018], p. 169, Fig. 6.6
Fig-E1-16: [Virtanen, 2018], p. 170, Fig. 6.7
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References

Audio

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Aud-E1-1: USM v2 dataset, Evaluation Set, Sound ID 2417
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Aud-E1-2: USM v2 dataset, Evaluation Set, Sound ID 1930

Aud-E1-3: USM v2 dataset, Evaluation Set, Sound ID 339

Aud-E1-4: G_M_D_THREE - CANAL_STREET_NEW_YORK_A011.wav (2018) - CC0 License,

https://freesound.org/people/G_M_D_THREE/sounds/424404



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Virtanen, T., Plumbley, M. D., & Ellis, D. (Eds.). (2018). Computational Analysis of Sound Scenes and Events. Cham, Switzerland: Springer International Publishing.

Lostanlen, V., Salamon, J., Cartwright, M., McFee, B., Farnsworth, A., Kelling, S., & Bello, J. P. (2019). Per-Channel Energy Normalization: Why and How. IEEE Signal Processing Letters, 26(1), 39–43.

