Machine Listening for Music and Sound Analysis

Lecture 6 - Environmental Sound Analysis 2

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https://machinelistening.github.io

Overview

- Acoustic Scene Classification
- Acoustic Anomaly Detection
- Real-World Deployment
  - Process Steps
  - Challenges
- Use-Cases
  - Urban Noise Monitoring
  - Traffic Monitoring
  - Industrial Sound Analysis
  - Context-sensitive Hearables
  - Bioacoustic Monitoring

Acoustic Scene Classification
Task

- Acoustic scene classification (ASC)
  - Multi-class (1 of N) classification scenario
  - Summative label (tagging)

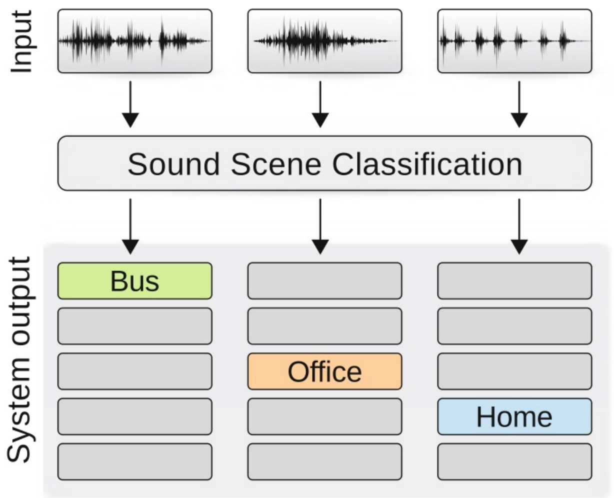


Fig. 1

Acoustic Scene Classification
Task

- Acoustic scene classification (ASC)
  - Multi-class (1 of N) classification scenario
  - Summative label (tagging)
- Acoustic scene
  - Typical set of sounds
  - Example: Office
    - Keyboard clicks
    - Human conversations
    - Printer
    - Air conditioner

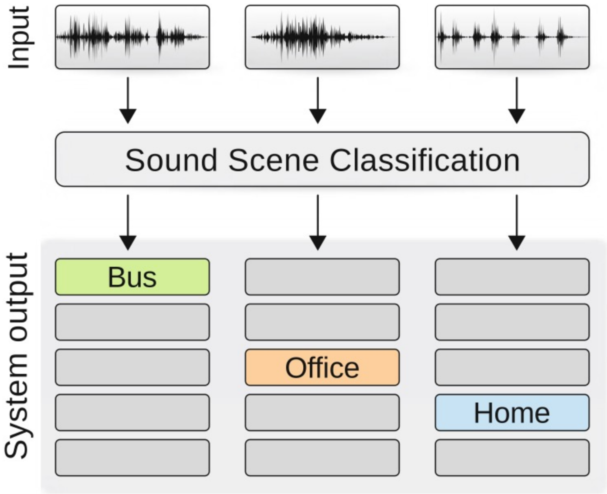


Fig. 1

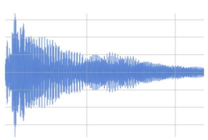
AUD-1

Fig. 2

Acoustic Scene Classification

Pipeline

- Label encoding
    - One-hot-encoded (global) target
- Example
    - 4 scene classes (bus, office, home, forest)
    - Encoding of an office recording



Own

$$\longrightarrow \underbrace{[\,0\quad 1\quad 0\quad 0\,]}_{\text{Sound classes}}$$

Acoustic Scene Classification
Pipeline

- Network architectures
  - Similar to SED (CNN & CRNN)
- Differences
  - Temporal result aggregation within network
  - Dense layer / pooling
  - Final layer: Softmax activation function (multiclass classification)

Acoustic Scene Classification
Pipeline

- Network architectures
  - Similar to SED (CNN & CRNN)
- Differences
  - Temporal result aggregation within network
  - Dense layer / pooling
  - Final layer: Softmax activation function (multiclass classification)
- Current Research Topics [Abeßer, 2020]
  - Attention → learn to focus on spectrogram regions
  - Open-set classification → detect unknown classes
  - Transfer learning → fine-tune pre-trained models with less data

Acoustic Anomaly Detection
Task

- Goal
  - Detect deviations from “normal” state
  - Is emitted sound from target object normal or anomalous?

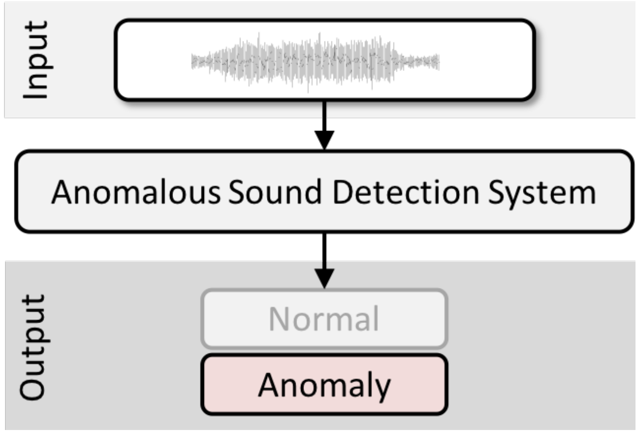


Fig. 3

Acoustic Anomaly Detection
Task

- Goal
    - Detect deviations from “normal” state
    - Is emitted sound from target object normal or anomalous?
- Challenges
    - Often only training examples for normal state available
    - Acoustic anomalies are often subtle compared to louder background noise

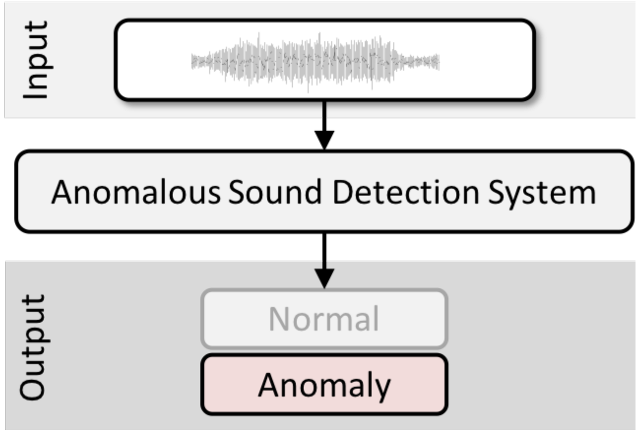


Fig. 3

Acoustic Anomaly Detection
Task

- Goal
  - Detect deviations from “normal” state
  - Is emitted sound from target object normal or anomalous?
- Challenges
  - Often only training examples for normal state available
  - Acoustic anomalies are often subtle compared to louder background noise
- Application Scenarios
  - Detecting machine failures
  - Intrusion detection (glass break…)

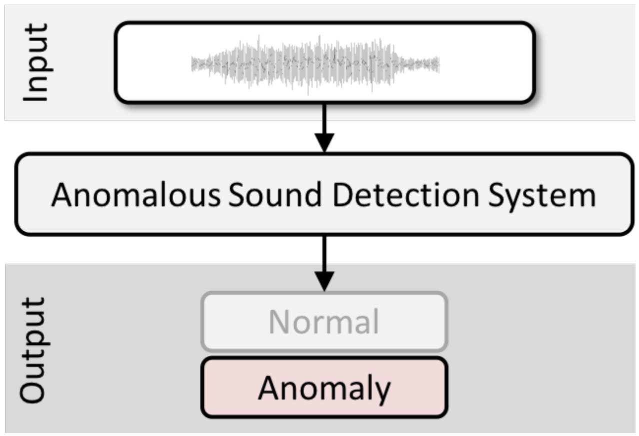


Fig. 3

Acoustic Anomaly Detection
Approaches

- Traditional methods
  - Distribution outlier detection
    - Modelling normal state distribution
    - Detect distribution outliers
    - E.g.: One-class GMM / SVM

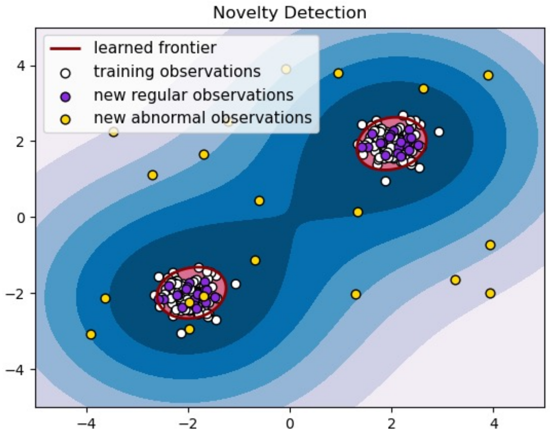


Fig. 4

Acoustic Anomaly Detection
Approaches

- Traditional methods
  - Distribution outlier detection
    - Modelling normal state distribution
    - Detect distribution outliers
    - E.g.: One-class GMM / SVM
  - Time-series analysis
    - AD via prediction error
    - E.g.: Autoregressive models, Hidden-Markov-Models (HMM)

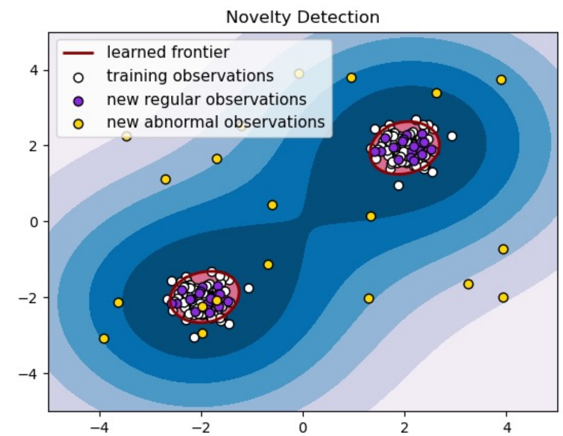


Fig. 4

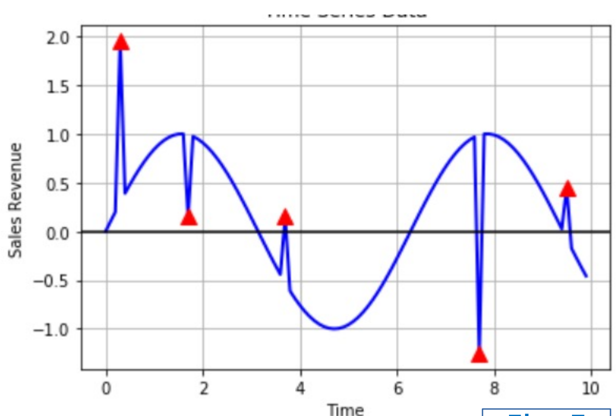
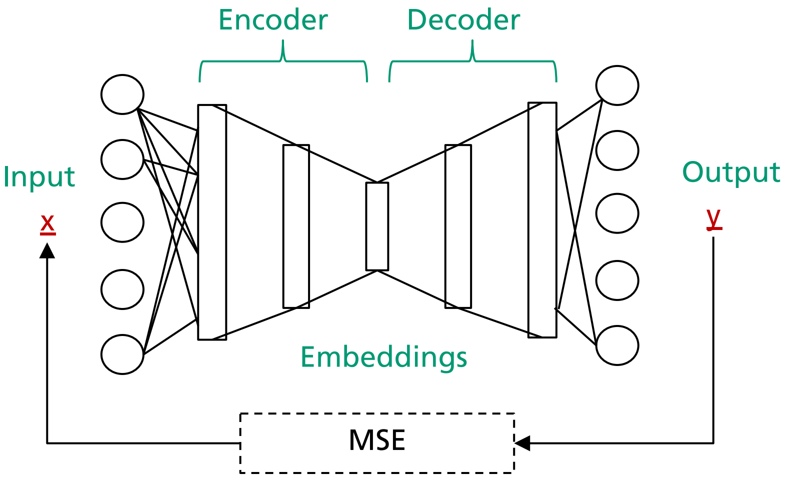


Fig. 5

Acoustic Anomaly Detection
Approaches

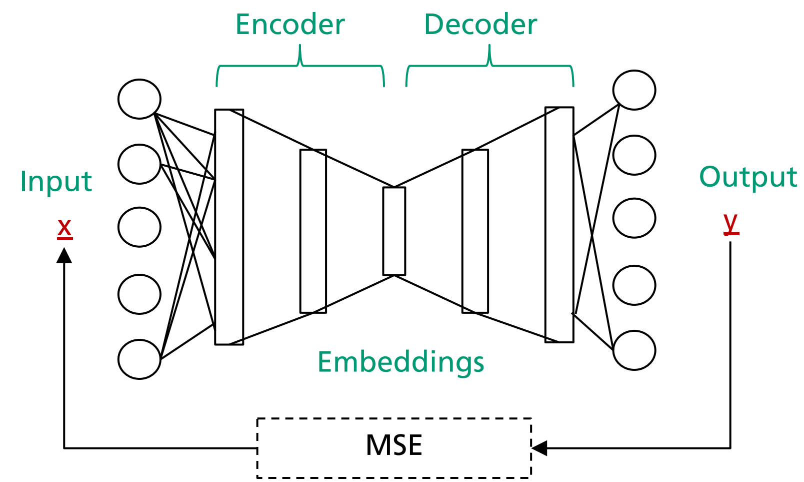
- Novel methods
  - Autoencoder (encoder → decoder) models
    - Idea:
      - Normal sounds can be better reconstructed than anomalous sounds



Own

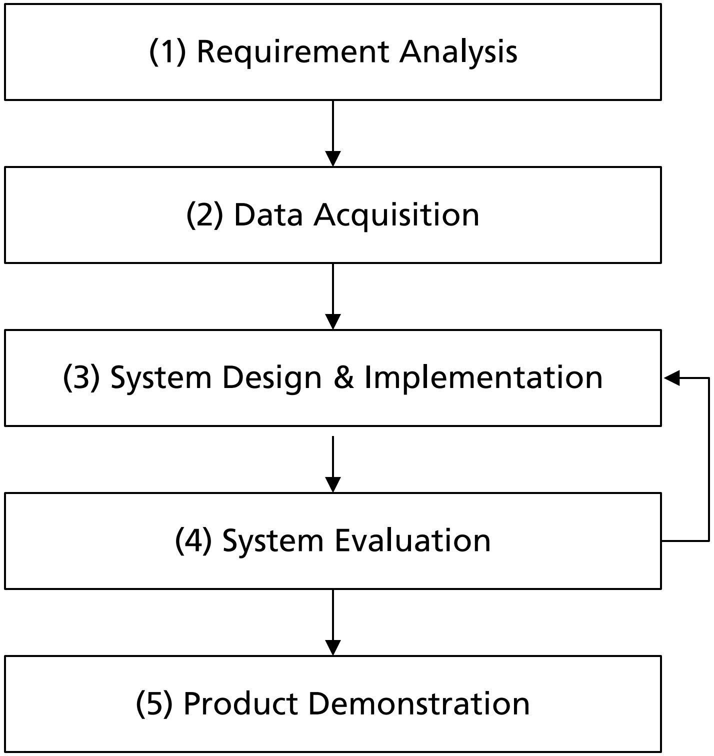
Acoustic Anomaly Detection
Approaches

- Novel methods
  - Autoencoder (encoder → decoder) models
    - Idea:
      - Normal sounds can be better reconstructed than anomalous sounds
    - Dense, convolutional, variational AE
    - Interpolation DNN
      - Interpolate spectrogram frame from surrounding frames



Own

Real-World Deployment
Project Phases



Own

Real-World Deployment
(1) Requirement Analysis

- Target application
- Research problem
    - Relevant sound classes

Real-World Deployment
(1) Requirement Analysis

- Target application
- Research problem
  - Relevant sound classes
- Performance requirements
  - Analysis window size
  - Metrics (accuracy, recall, precision, f-score, etc.)
- User Experience
  - Error type categorization / prioritization

Real-World Deployment
(1) Requirement Analysis (Example)

- Target application (context-aware cell phones)
    - Main characteristics (ringtone type & loudness adapts to user's environment)

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  - Relevant sound classes (at home, opera, traffic …)

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(1) Requirement Analysis (Example)

- Target application (context-aware cell phones)
  - Main characteristics (ringtone type & loudness adapts to user's environment)
- Research problem (acoustic scene classification)
  - Relevant sound classes (at home, opera, traffic …)
- Performance requirements
  - Analysis window size (5s)
  - Metrics (accuracy, recall, precision, f-score, etc.) (F > 0.85)

Real-World Deployment
(1) Requirement Analysis (Example)

- Target application (context-aware cell phones)
  - Main characteristics (ringtone type & loudness adapts to user's environment)
- Research problem (acoustic scene classification)
  - Relevant sound classes (at home, opera, traffic …)
- Performance requirements
  - Analysis window size (5s)
  - Metrics (accuracy, recall, precision, f-score, etc.) (F > 0.85)
- User Experience
  - Error type categorization / prioritization
    - (confusion opera ⟷ traffic worse than traffic ⟷ at home)

Real-World Deployment
(1) Requirement Analysis

- Performance constraints
  - Computer platform (Raspberry 4, Jetson Nano, etc.)
  - Memory, CPU / GPU performance
  - Inference time vs. real-time

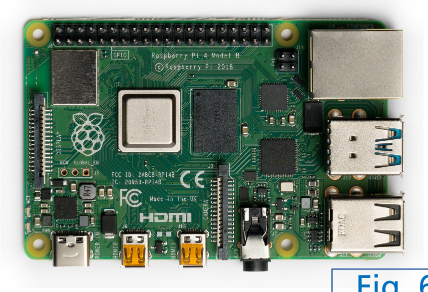

Fig. 6

Rhaspberry 4

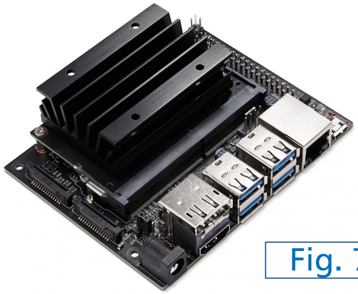

Fig. 7

Jetson Nano

Real-World Deployment
(1) Requirement Analysis

- Performance constraints
  - Computer platform (Raspberry 4, Jetson Nano, etc.)
  - Memory, CPU / GPU performance
  - Inference time vs. real-time
- Model constraints
  - Architecture
  - # Parameters
  - # Layers
  - Model size
  - Floating-point resolution

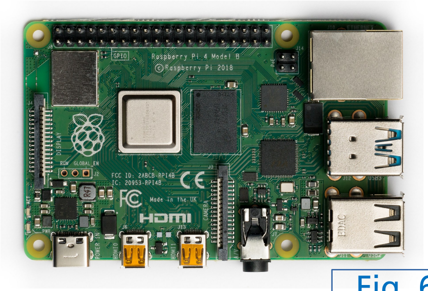

Fig. 6

Rhaspberry 4

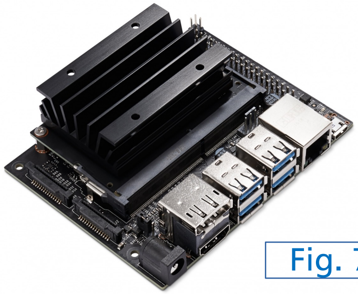

Fig. 7

Jetson Nano

Real-World Deployment
(2) Data Acquisition

- Preliminary considerations
  - Acoustic conditions at deployment scenario / target use-case
    - Room size / characteristics, echoes / feedback, background noises
  - Target sound variability

Fig. 8

Real-World Deployment
(2) Data Acquisition

- Preliminary considerations
    - Acoustic conditions at deployment scenario / target use-case
        - Room size / characteristics, echoes / feedback, background noises
    - Target sound variability
    - Sensor placement
    - Recording procedure
        - Microphone type / setup
        - (Background noise removal)

Fig. 8

Real-World Deployment
(2) Data Acquisition

- Preliminary considerations
  - Acoustic conditions at deployment scenario / target use-case
    - Room size / characteristics, echoes / feedback, background noises
  - Target sound variability
  - Sensor placement
  - Recording procedure
    - Microphone type / setup
    - (Background noise removal)
  - Security / Privacy
  - Data transmission / storage

Fig. 8

Real-World Deployment
(2) Data Acquisition

- Audio Recording

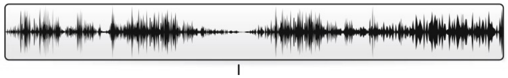

Fig. 9

Real-World Deployment
(2) Data Acquisition

- Audio Recording
- Annotation
  - Time / labor expensive
  - Contextual metadata (time, location, …)
  - Granularity (segment vs. file-level)
  - Subjectivity (annotator agreement)
  - Use existing tools (e.g., Sonic Visualiser)

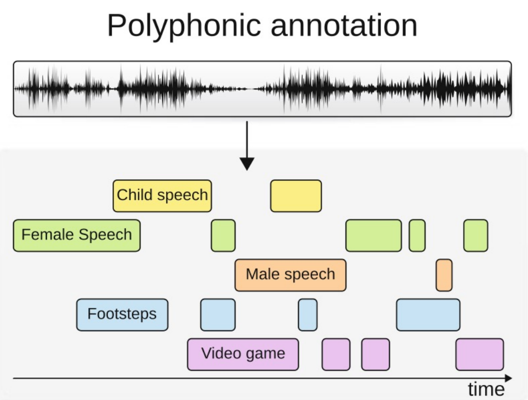

Fig. 9

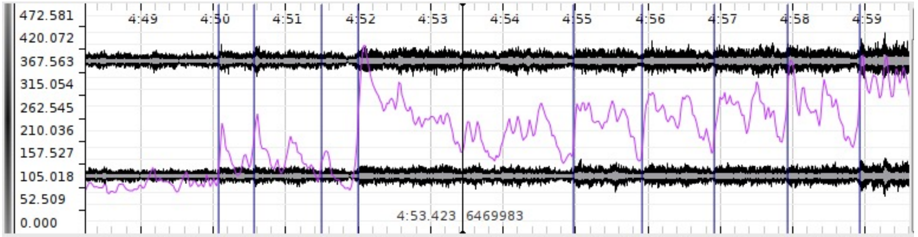

Fig. 10

Real-World Deployment
(2) Data Acquisition

- Audio Recording
- Annotation
    - Time / labor expensive
    - Contextual metadata (time, location, …)
    - Granularity (segment vs. file-level)
    - Subjectivity (annotator agreement)
    - Use existing tools (e.g., Sonic Visualiser)
- Data split
    - Train / Validation / Test

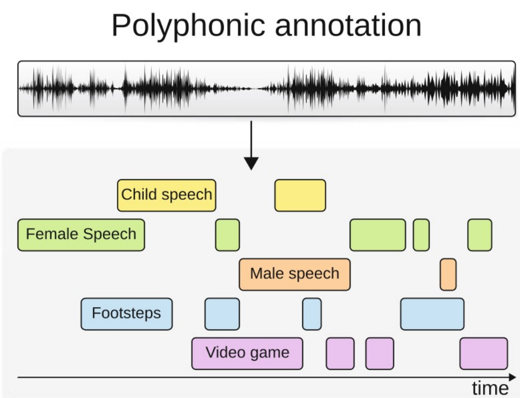

Fig. 9

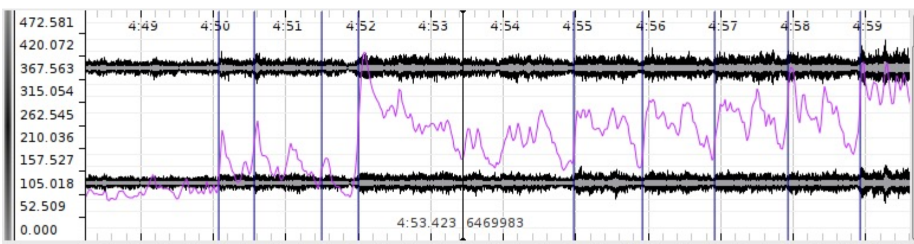

Fig. 10

Real-World Deployment
(3) System Design & Implementation

- Goal → Proof-of-Concept (PoC)
    - Solves defined problem
    - Demonstrate capability / feasibility under laboratory environment (datasets)

Real-World Deployment
(3) System Design & Implementation

- Goal → Proof-of-Concept (PoC)
  - Solves defined problem
  - Demonstrate capability / feasibility under laboratory environment (datasets)
- Quickly implement baseline system (reference point)
- Iterative improvement of system components
  - Audio processing (pre-processing, feature extraction)
  - Machine learning (learning / recognition / detection)

Real-World Deployment
(4) System Evaluation

- Goal → Realistic performance estimate
  - Ideally test condition & target application are similar
  - Compare to baseline system / state-of-the-art methods

Real-World Deployment
(4) System Evaluation

- Goal → Realistic performance estimate
  - Ideally test condition & target application are similar
  - Compare to baseline system / state-of-the-art methods
- Incremental changes & evaluation
  - Identify most important factors that influence the system's performance
- Evaluation
  - Offline (pre-recorded audio) vs. online (real-time recordings)
  - Objective (test dataset, defined metrics) vs. subjective (user tests)

Real-World Deployment
(5) Product Demonstration

- Goal → Develop PoC further into a Prototype
    - Key features according to requirement analysis
    - Tested in realistic use-cases (technology validation)
    - Tested with real users (user experience / perception of good performing system)

Real-World Deployment
(5) Product Demonstration

- Goal → Develop PoC further into a Prototype
    - Key features according to requirement analysis
    - Tested in realistic use-cases (technology validation)
    - Tested with real users (user experience / perception of good performing system)
- Iterative development until ready for deployment
    - Problem examples: too high latency, too low noise-robustness
- Finally
    - System integration (user interface etc.)
    - Deployed to the market (small scale pilot -> full scale)

Real-World Deployment
Challenges

- Data Mismatch / Domain Shift
- Model Complexity
- Privacy / Security

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Differences in data distribution due to
    - Room acoustics (reverb, reflections)
    - Microphone characteristics (frequency response, directionality)

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Differences in data distribution due to
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- Domain adaptation
  - Adapt model / feature mapping from source to target domain
    - Unsupervised: adversarial training [Gharib, 2018]
    - Supervised: transfer learning

Real-World Deployment
(1) Data Mismatch / Domain Shift

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  - Room acoustics (reverb, reflections)
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- Domain adaptation
  - Adapt model / feature mapping from source to target domain
    - Unsupervised: adversarial training [Gharib, 2018]
    - Supervised: transfer learning
- Data augmentation
  - Increase model robustness by increasing data variability
- Data normalization [Johnson, 2020] [Latifi, 2023]
  - Align source and target data distributions

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Domain adaptation (DA)
  - Unsupervised DA via adversarial training [Gharib, 2018]

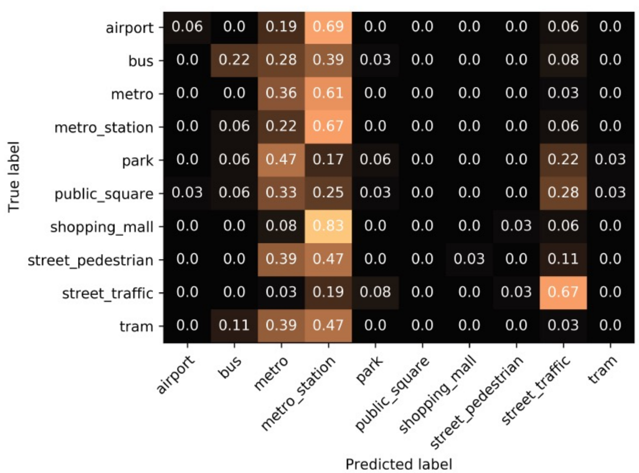

Fig. 11

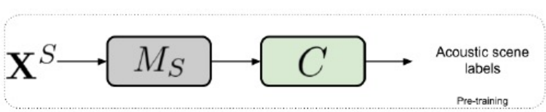

Fig. 12

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Domain adaptation (DA)
  - Unsupervised DA via adversarial training [Gharib, 2018]

True label \ Predicted label	airport	bus	metro	metro_station	park	public_square	shopping_mall	street_pedestrian	street_traffic	tram
airport	0.06	0.0	0.19	0.69	0.0	0.0	0.0	0.0	0.06	0.0
bus	0.0	0.22	0.28	0.39	0.03	0.0	0.0	0.0	0.08	0.0
metro	0.0	0.0	0.36	0.61	0.0	0.0	0.0	0.0	0.03	0.0
metro_station	0.0	0.06	0.22	0.67	0.0	0.0	0.0	0.0	0.06	0.0
park	0.0	0.06	0.47	0.17	0.06	0.0	0.0	0.0	0.22	0.03
public_square	0.03	0.06	0.33	0.25	0.03	0.0	0.0	0.0	0.28	0.03
shopping_mall	0.0	0.0	0.08	0.83	0.0	0.0	0.0	0.03	0.06	0.0
street_pedestrian	0.0	0.0	0.39	0.47	0.0	0.0	0.03	0.0	0.11	0.0
street_traffic	0.0	0.0	0.03	0.19	0.08	0.0	0.0	0.03	0.67	0.0
tram	0.0	0.11	0.39	0.47	0.0	0.0	0.0	0.0	0.03	0.0

Fig. 11

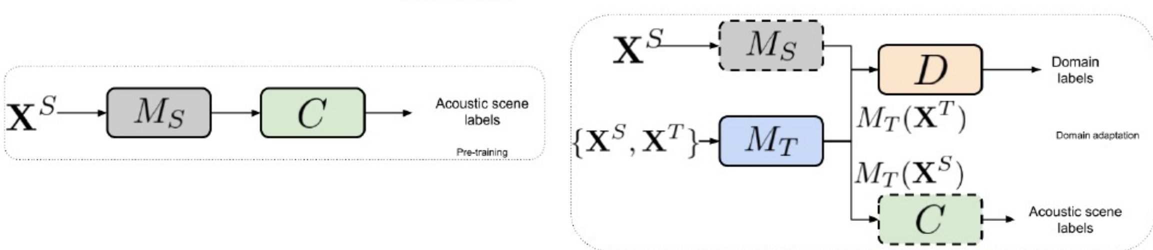

Fig. 12

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Domain adaptation (DA)
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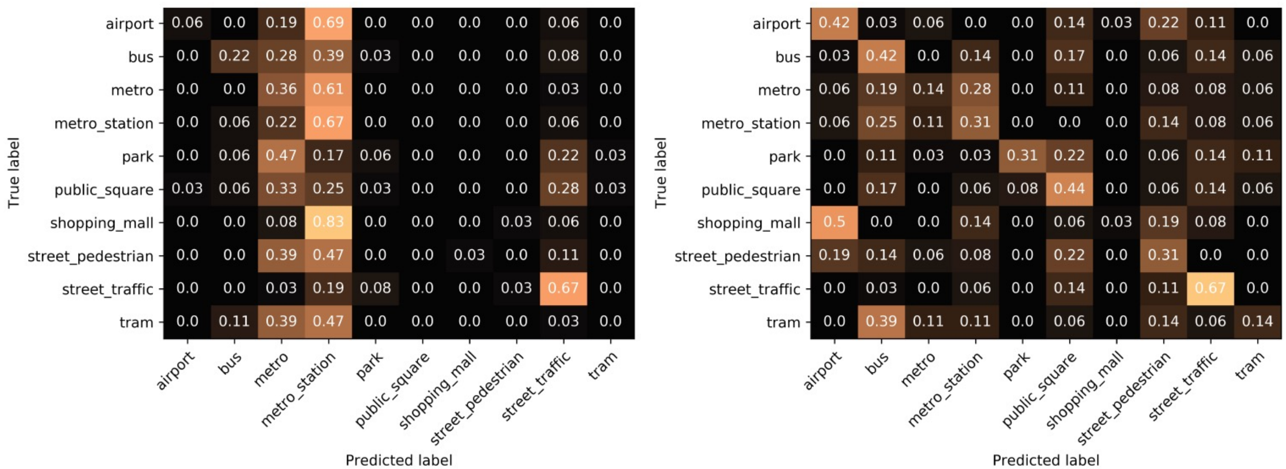

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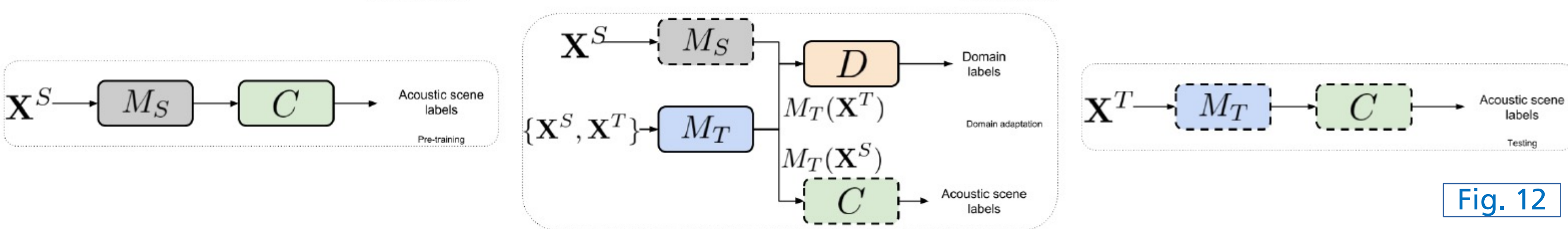
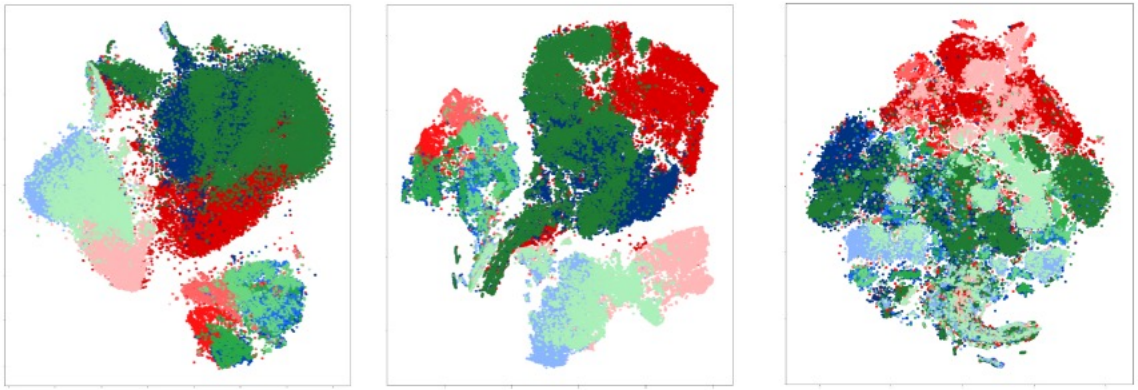


Fig. 12

Real-World Deployment
(1) Data Mismatch / Domain Shift

- Data normalization
  - Align source and target data distribution (zero mean & standard deviations) [Johnson, 2020]
    - Reduce domain shift

Metal ball surface classification (colors = classes, shadings = recordings)



(a) No Norm (b) Global Norm (c) Adaptive Norm

Fig. 13

Real-World Deployment
(2) Model Complexity

- Goals
  - Reduce model size – fewer parameters, less memory required
  - Reduce latency (inference time) / lower energy consumption

Real-World Deployment
(2) Model Complexity

- Goals
  - Reduce model size – fewer parameters, less memory required
  - Reduce latency (inference time) / lower energy consumption

- Approaches ([Wang, 2021])
  - Pruning
    - Identify & remove redundant connections / neurons

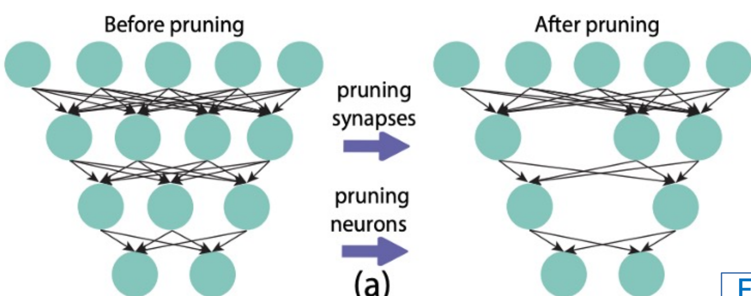


Fig. 14

Real-World Deployment
(2) Model Complexity

- Approaches
  - Quantization
    - Reduce numeric precision while minimize information loss
      - Ex.: 32-bit floating point -> 8-bit fixed point (256 values)
    - Reduce memory footprint of network weights

Real-World Deployment
(2) Model Complexity

- Approaches
  - Quantization
    - Reduce numeric precision while minimize information loss
      - Ex.: 32-bit floating point -> 8-bit fixed point (256 values)
    - Reduce memory footprint of network weights
  - Low-rank tensor decompositions
    - Replace (many) redundant filters by a linear combination of fewer filters

Real-World Deployment
(2) Model Complexity

- Approaches
  - Quantization
    - Reduce numeric precision while minimize information loss
      - Ex.: 32-bit floating point -> 8-bit fixed point (256 values)
    - Reduce memory footprint of network weights
  - Low-rank tensor decompositions
    - Replace (many) redundant filters by a linear combination of fewer filters
  - Knowledge Distillation
    - Transfer knowledge from complex (teacher) to simpler (student) model

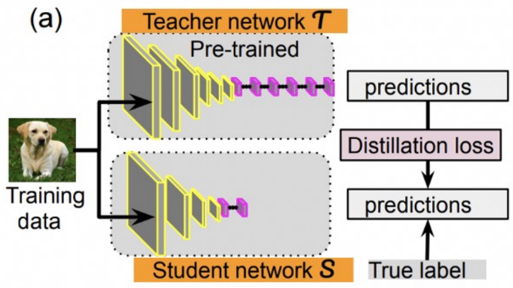


Fig. 15

Real-World Deployment
(3) Privacy / Data Protection and Data Security

- Depending on the specific application, challenges include e.g.
  - Avoiding processing and storage of speech content and speaker characteristics (person-related information)
  - Ensuring authenticity of recordings, and recording time / location

Real-World Deployment
(3) Privacy / Data Protection and Data Security

- Depending on the specific application, challenges include e.g.
  - Avoiding processing and storage of speech content and speaker characteristics (person-related information)
  - Ensuring authenticity of recordings, and recording time / location
  - Ensuring confidentiality of recordings, annotations and models during storage, transmission and (sometimes) training
  - Avoiding replay attacks

Real-World Deployment
(3) Privacy / Data Protection and Data Security

- Countermeasures
    - Data anonymization (speech filtering / scrambling, etc.)
    - Data authentication, encryption and key management (based on security standards and cryptography)

Real-World Deployment
(3) Privacy / Data Protection and Data Security

- Countermeasures
  - Data anonymization (speech filtering / scrambling, etc.)
  - Data authentication, encryption and key management (based on security standards and cryptography)
  - Secure Federated Learning (incl. FHE and Differential Privacy)
  - Replay detection

Application Scenarios
(1) Urban Noise Monitoring

Fig. 16

- Joint R&D project (2016 – 2018)
    - Fraunhofer IDMT, IMMS, SSJ GmbH, BE
- Goal
    - Develop distributed sensor network for
        - Sound level measurement
        - Sound classification

Fig. 17

Application Scenarios
(1) Urban Noise Monitoring

Fig. 16

- Joint R&D project (2016 – 2018)
  - Fraunhofer IDMT, IMMS, SSJ GmbH, BE
- Goal
  - Develop distributed sensor network for
    - Sound level measurement
    - Sound classification
- Approach
  - Mobile sensor units
    - Raspberry Pi 3, quad-core ARM, 1GB RAM
    - Battery + MEMS microphones
    - Sensor locations (light poles)

Fig. 17

Fig. 18

Application Scenarios
(1) Urban Noise Monitoring

- Measurements
  - Different loudness values (8/s)
  - Sound event detection (1/s)
    - 9 sound event classes (car, conversation, music, roadworks, siren, train, tram, truck, wind)

Spectrogram examples (2 s long)

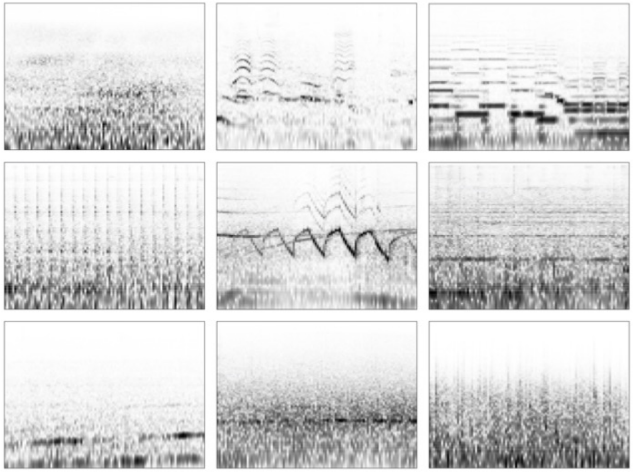


Fig. 19

Application Scenarios
(1) Urban Noise Monitoring

- Measurements
    - Different loudness values (8/s)
    - Sound event detection (1/s)
        - 9 sound event classes (car, conversation, music, roadworks, siren, train, tram, truck, wind)

Spectrogram examples (2 s long)

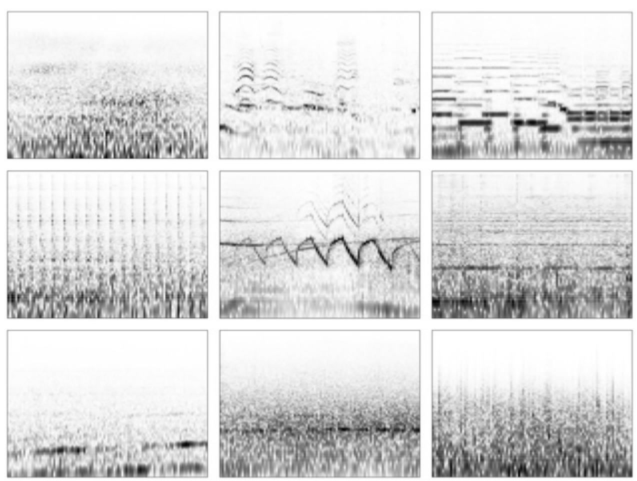


Fig. 19

- CNN architecture

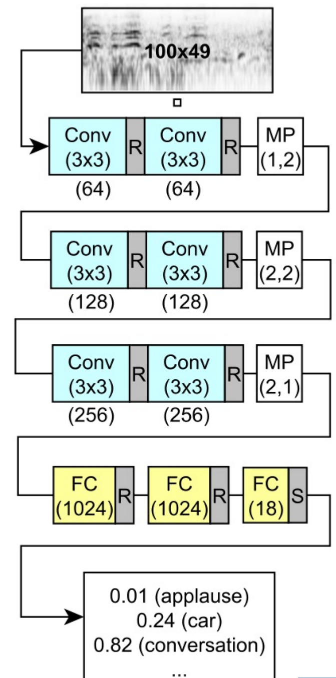
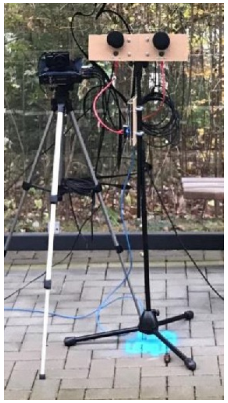


Fig. 20

Application Scenarios
(2) Traffic Monitoring

- Tasks
  - Vehicle detection
  - Direction of movement estimation
  - Speed estimation
  - Vehicle type classification
    - Car, truck, bus, motorcycle etc.

Fig. 21



Application Scenarios
(2) Traffic Monitoring

- Tasks
  - Vehicle detection
  - Direction of movement estimation
  - Speed estimation
  - Vehicle type classification
    - Car, truck, bus, motorcycle etc.
- Challenges
  - Microphone type
  - Local acoustic conditions
  - Vehicle speed
  - Street surface quality & weather conditions

Fig. 21

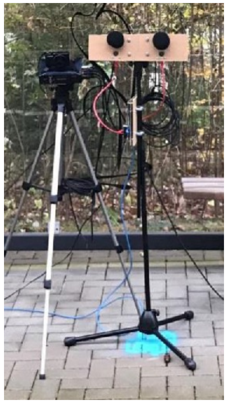


Fig. 22

Application Scenarios
(2) Traffic Monitoring

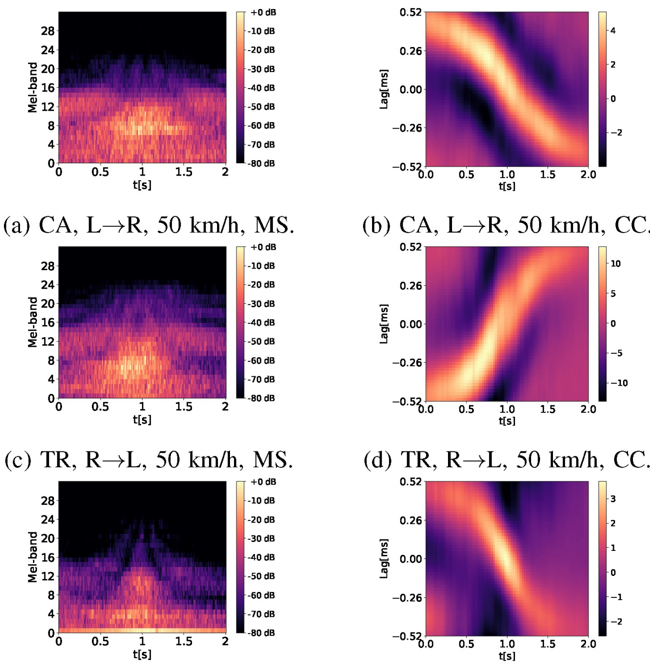
- Audio Features
    - Vehicle detection & direction of movement & speed
        - Channel cross-correlation
    - Vehicle type classification
        - Mel spectrogram
- Neural network architectures (#parameters)
    - CNNs (1,1 – 3,2 mio.)
    - MobileNetMini (15,000)

Application Scenarios
(2) Traffic Monitoring

- Audio Features
  - Vehicle detection & direction of movement & speed
    - Channel cross-correlation
  - Vehicle type classification
    - Mel spectrogram
- Neural network architectures (#parameters)
  - CNNs (1,1 – 3,2 mio.)
  - MobileNetMini (15,000)
- Example (truck, car, motorcycle)
  - 2s clips (IDMT-Traffic dataset)

Mel spectrogram | Stereo channel cross-correlation

Car | Truck | Motorcycle



(a) CA, L→R, 50 km/h, MS. (b) CA, L→R, 50 km/h, CC.
(c) TR, R→L, 50 km/h, MS. (d) TR, R→L, 50 km/h, CC.
(e) MC, L→R, ≈ 70 km/h, MS. (f) MC, L→R, ≈ 70 km/h, CC.

AUD-2

Fig. 23

Application Scenarios
(3) Industrial Sound Analysis

- Challenges
  - Real-time analysis & classification of industrial sounds
  - Energy-efficient AI algorithms
  - Sound variations due to different machine states
  - Acoustic anomalies subtle compared to background noises

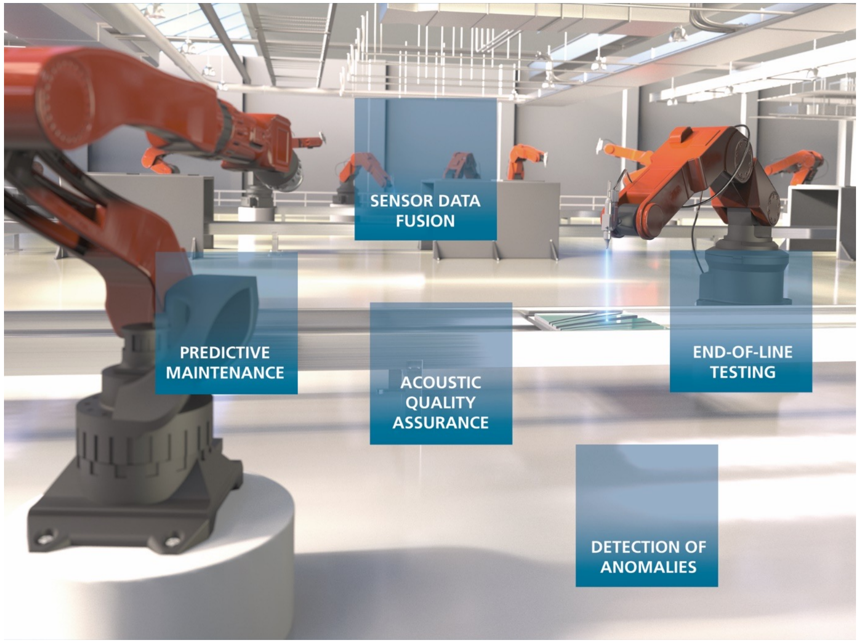
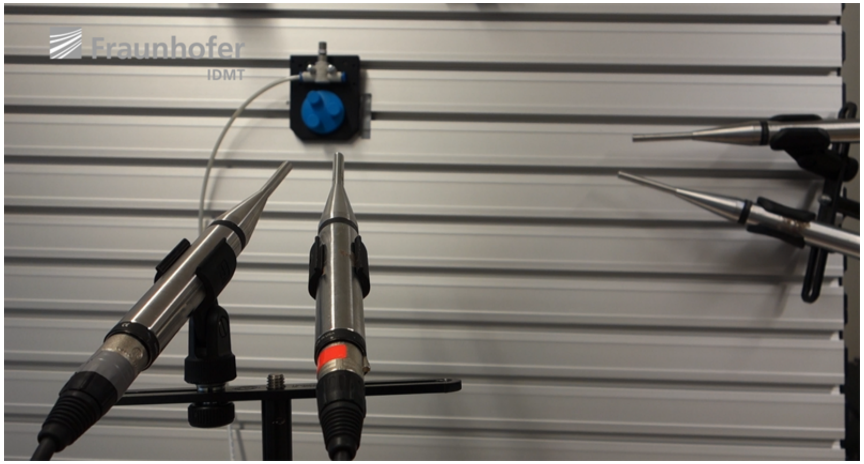


Fig. 24

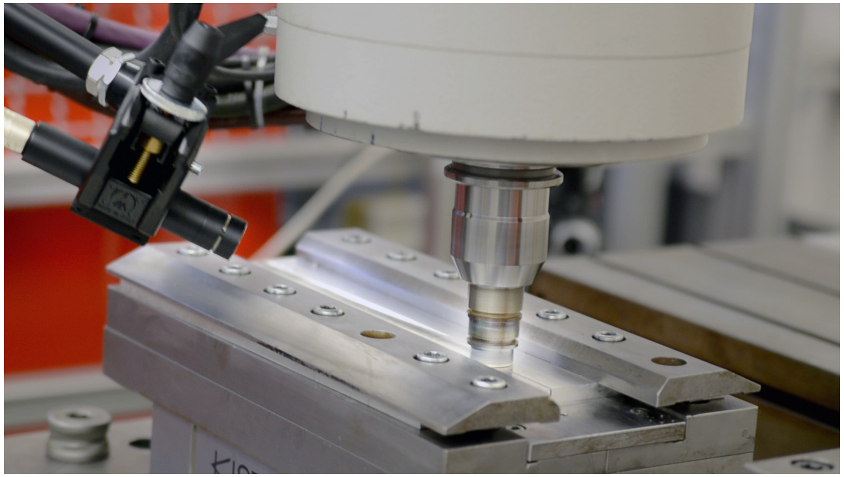
Application Scenarios
(3) Industrial Sound Analysis

- Example use-cases @ Industrial Media Applications (Fraunhofer IDMT)



Compressed Air Leakage Detection

Fig. 25



Friction Stir Welding

Fig. 26

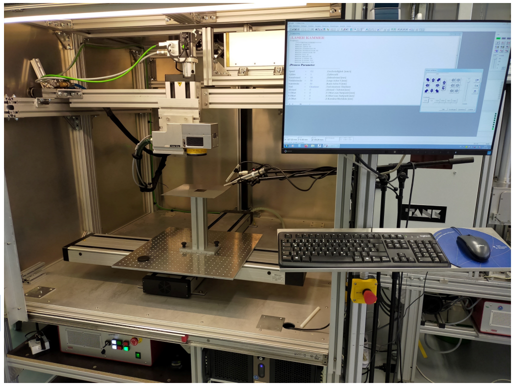


Fig. 27

Laser Ablation Machine

Application Scenarios
(4) Context-Sensitive Hearables

- Wireless earbuds, hearing aids
- Functionality
  - Context-awareness
    - Detect listeners location / activity (ASC)
      - E.g.: At home, traffic, subway, restaurant, sport
    - Detect relevant sound events (SED):
      - E.g.: Siren, honking, scream

Application Scenarios
(4) Context-Sensitive Hearables

- Wireless earbuds, hearing aids
- Functionality
  - Context-awareness
    - Detect listeners location / activity (ASC)
      - E.g.: At home, traffic, subway, restaurant, sport
    - Detect relevant sound events (SED):
      - E.g.: Siren, honking, scream
  - Background noise reduction
  - Dynamic volume adjustments
  - (Immersive listening experience)

Application Scenarios
(5) Bioacoustic Monitoring

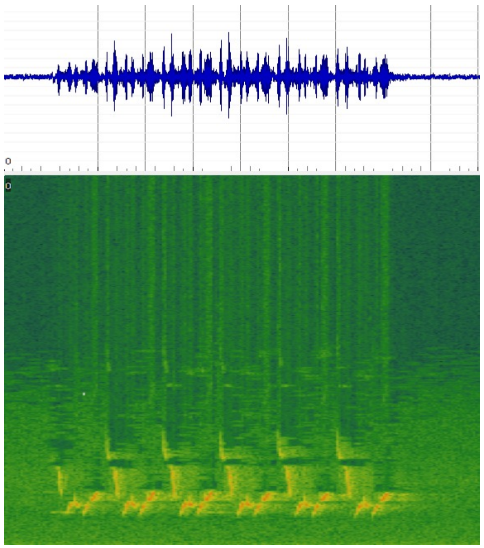
- Autonomous acoustic sensors
  - Non-intrusive
  - Allow for long-term recordings (days / weeks …)
- Monitored species: birds, primates, bees, marine mammals, etc.

Application Scenarios
(5) Bioacoustic Monitoring

- Autonomous acoustic sensors
  - Non-intrusive
  - Allow for long-term recordings (days / weeks …)
- Monitored species: birds, primates, bees, marine mammals, etc.
- Monitor
  - Population sizes / migration patterns
- Challenges for SED
  - High variability even within sounds classes
  - Large amounts of unlabelled data (annotation requires expert knowledge)
    - Few-shot learning (DCASE 2021, task 5)

Application Scenarios
(5) Bioacoustic Monitoring

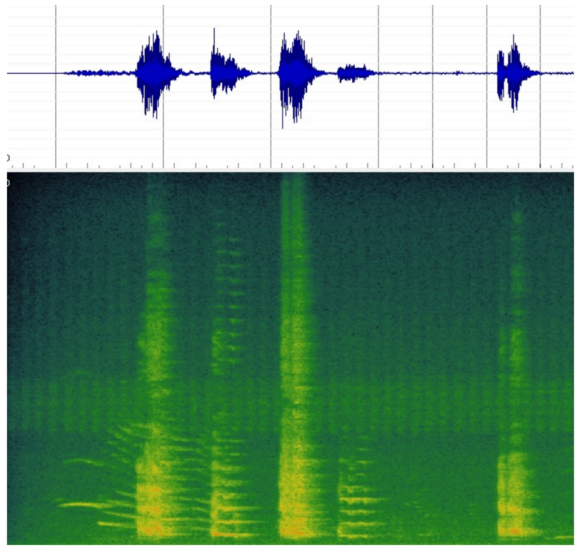
- Bird sound detection → detection / classification / counting



AUD-3

Fig. 28

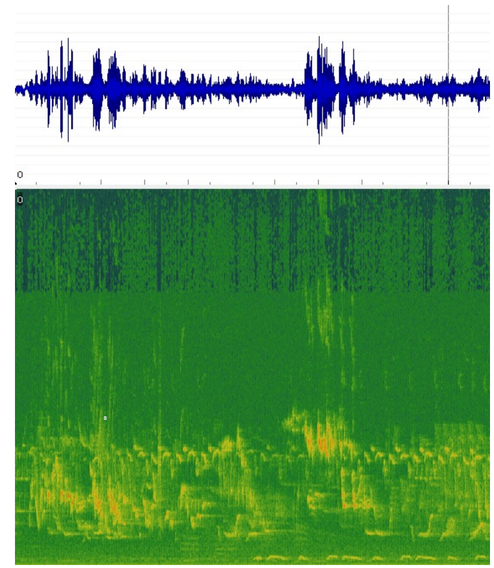
Carolina Wren



AUD-4

Flamingo

Fig. 29



AUD-5

Dawn chorus
(bird ensemble)

Summary

- Acoustic Scene Classification
- Acoustic Anomaly Detection
- Real-World Deployment
    - Process Steps
    - Challenges
- Use-Cases
    - Urban Noise Monitoring
    - Traffic Monitoring
    - Industrial Sound Analysis
    - Context-sensitive Hearables
    - Bioacoustic Monitoring

Computational Analysis of Sound and Music

- Novel lecture in summer semester 2024!

	Week	Date 1	Date 2
I. Foundations	1	Audio	Audio
	2	Audio	ML/DL
	3	ML/DL	ML/DL
II. Applications	4	Music Information Retrieval	
	5		
	6		
	7	Environmental Sound Analysis	
	8		
III. Research Project	9	Intro / Topics	Literature research
	10	Datasets	ML/DL pipeline
	11	Evaluation/metrics	Visualization/Paper writing
	12	Wrap-Up, Paper Deadline	Project presentation, Q/A

References

Abeßer, J. et al. (2018). A Distributed Sensor Network for Monitoring Noise Level and Noise Sources in Urban Environments. *Proceedings of the 6th IEEE International Conference on Future Internet of Things and Cloud (FiCloud)*, 318–324. Barcelona, Spain.

Abeßer, J., et al. (2019). Urban Noise Monitoring in the Stadtlärm Project - A Field Report. *Proceedings of the Detection and Classification of Acoustic Scenes and Events (DCASE)*. New York, NY, USA.

Abeßer, J. (2020). A Review of Deep Learning Based Methods for Acoustic Scene Classification. *Applied Sciences*, *10*(6).

Abeßer, J., Gourishetti, S., Kátai, A., Clauß, T., Sharma, P., & Liebetrau, J. (2021). IDMT-Traffic: An Open Benchmark Dataset for Acoustic Traffic Monitoring Research. *Proceedings of the European Signal Processing Conference (EUSIPCO)*. Dublin, Ireland.

Gharib, S., Drossos, K., Emre, C., Serdyuk, D., & Virtanen, T. (2018). Unsupervised Adversarial Domain Adaptation for Acoustic Scene Classification. *Proceedings of the Detection and Classification of Acoustic Scenes and Events (DCASE)*. Surrey, UK.

Howard, A. G., et al. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *ArXiv Preprint ArXiv:1704.04861*.

Johnson, D. S., & Grollmisch, S. (2021). Techniques improving the robustness of deep learning models for industrial sound analysis. *Proceedings of the European Processing Conference (EUSIPCO)*, 81–85. Amsterdam, The Netherlands.

Signal

References

Bidarouni, A. L. & Abeßer, J. (2023). Unsupervised Feature-Space Domain Adaptation applied for Audio Classification. Proceedings of the International Symposium on the Internet of Sounds (IoS-RN)

Stowell, D., Petrusková, T., Šálek, M., & Linhart, P. (2018). Automatic acoustic identification of individual animals: Improving generalisation across species and recording conditions. *ArXiv Preprint ArXiv:1810.09273*.

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

Wang, L., & Yoon, K. J. (2021). Knowledge Distillation and Student-Teacher Learning for Visual Intelligence: A Review and New Outlooks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *14*(8), 1–40.

Images

Fig. 1: [Virtanen, 2018], p. 267, fig. 9.7

Fig. 2: https://images.theconversation.com/files/349387/original/file-20200724-15-ldrybi.jpg

Fig. 3: http://dcase.community/challenge2020/task-unsupervised-detection-of-anomalous-sounds (Figure 1)

Fig. 4: https://scikit-learn.org/stable/_images/sphx_glr_plot_oneclass_0011.png

Fig. 5: https://miro.medium.com/max/722/1*TvZ9jI9vGX-fWwc3AHwNDw.png

Fig. 6: https://en.wikipedia.org/wiki/Raspberry_Pi#/media/File:Raspberry_Pi_4_Model_B_-_Top.jpg

Fig. 7: https://developer.nvidia.com/sites/default/files/akamai/embedded/images/jetsonNano/JetsonNano-DevKit_Front-Top_Right_trimmed.jpg

Fig. 8: https://www.idmt.fraunhofer.de/content/dam/idmt/documents/IL/IMA/AI4Edge_DE.pdf (cover image)

Fig. 9: [Virtanen, 2018], p. 154, fig. 6.2, right

Fig. 10: https://www.sonicvisualiser.org/doc/reference/1.7.2/en/images/pane-layers.png

Fig. 11: [Gharib, 2018], p. 3., fig. 2 (a) & (b)

Fig. 12: [Gharib, 2018], p. 2., fig. 1

Images

Fig. 13: IMG-13: Johnson & Grollmisch: Techniques improving the robustness of deep learning models for industrial sound analysis, EUSIPCO 2021, Fig. 1, p.82

Fig. 14: https://miro.medium.com/max/955/1*C3rR1-qzZfgYE_QA7WvLOQ.png

Fig. 15: [Wang, 2021], p. 2, fig. 1 (a)

Fig. 16: https://stadtlaerm.de/pics/talaerm.svg

Fig. 17: [Abeßer, 2019], p. 2, fig. 2

Fig. 18: [Abeßer, 2018], p. 3, fig. 2

Fig. 19: [Abeßer, 2019], p.3, fig. 3

Fig. 20: [Abeßer, 2018], p.5, fig. 4

Fig. 21 & 22: [Abeßer, 2021], p.3, fig. 1, (b, c, d) source images

Fig. 23: [Abeßer, 2021], p.3, fig. 2

Fig. 24-27: Fraunhofer IDMT

Fig. 28: https://www.allaboutbirds.org/guide/assets/photo/304470861-1280px.jpg

Fig. 29: https://cdn.download.ams.birds.cornell.edu/api/v1/asset/54167691/1800

Sounds

AUD-1: https://freesound.org/people/16HPanskaTyllova_Terezie/sounds/497363

AUD-2: Three clips from IDMT-Traffic dataset [Abeßer, 2021]

AUD-3: https://freesound.org/people/IFartInUrGeneralDirection/sounds/96195/

AUD-4: https://freesound.org/people/InspectorJ/sounds/400860/

AUD-5: https://freesound.org/people/Simon%20Spiers/sounds/516876/

Thank you!

- Any questions?

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