# Deep Neural Networks for Multiple Speaker Detection and Localization

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### Introduction

#### Task: Sound source localization in real HRI scenarios

unknown number of multiple speakers





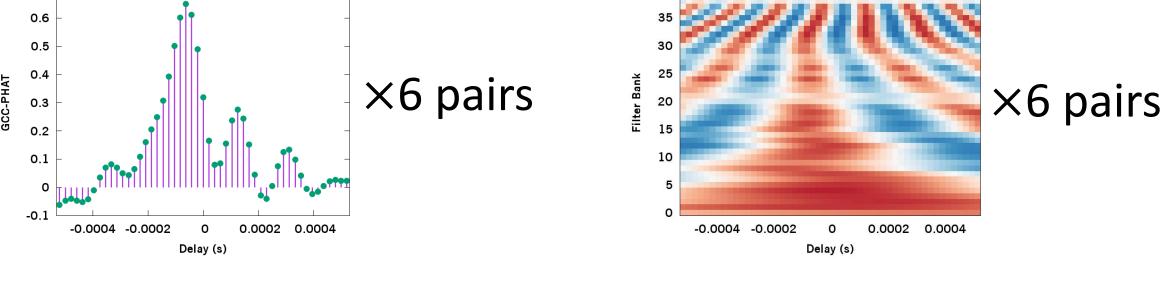
#### **Contributions:**

- Novel deep learning-based multiple sound source localization method.
- Likelihood-based output encoding handles an arbitrary number of sources.
- Investigation of three network architectures based on different motivations.
- Study sub-band cross correlation information as an input feature for better localization cues in speech mixtures.
- Collected and released a benchmark dataset of real recordings.

## Approach

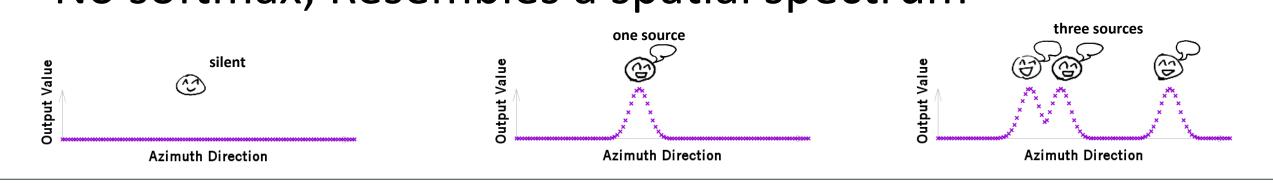
## 4-channel audio Neural Network Localize Features

# Features: Cross-correlation between pairs of microphones **GCC-PHAT** coefficients **GCC-PHAT** on filter bank



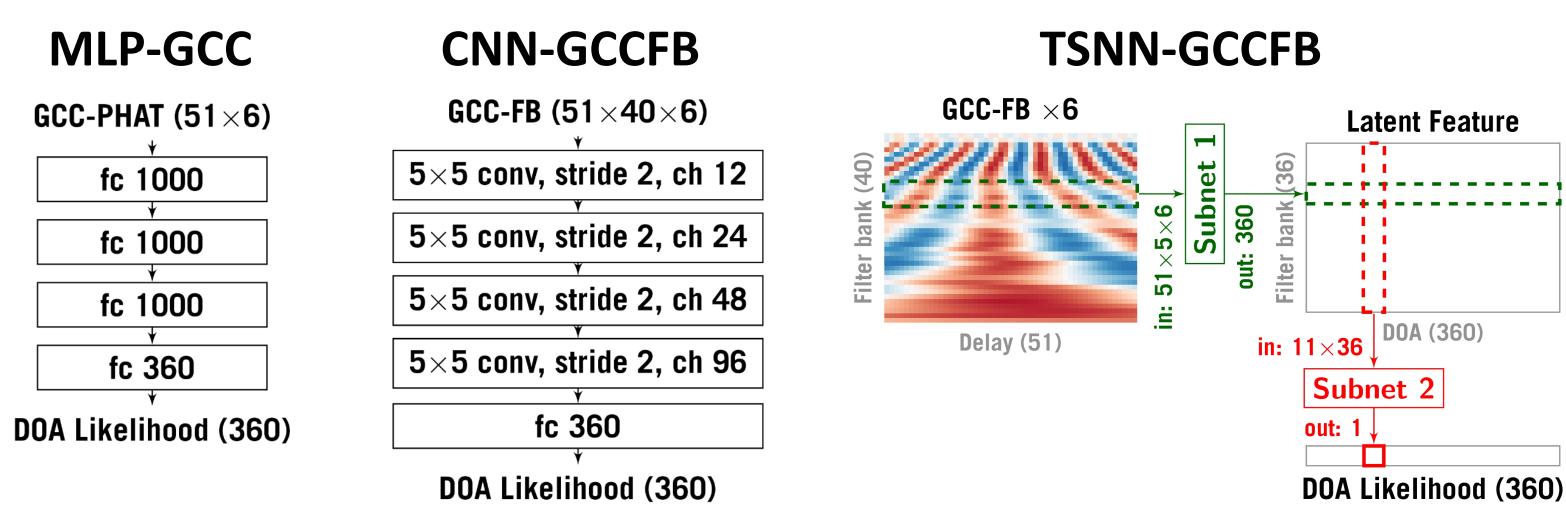
## Output: Likelihood of sound source being in each direction

- **Encoding:** Gaussian functions around true sources
- **Decoding:** Finding peaks
- No softmax; Resembles a spatial spectrum



#### Different network architectures:

- Multi-layer Perceptron (MLP-GCC)
- Basic structure (baseline)
- **Convolutional neural network (CNN-GCCFB)**
- Convolution to reduce number of parameters
- Two-stage network (TSNN-GCCFB):
- Considers the sparsity of speech signal in time-frequency points
- First predict on sub-bands
- Then aggregate early predictions across all frequencies.
- Training also in 2 steps: (1) Pretrain first subnet (2) End-to-end



## **Experiments**

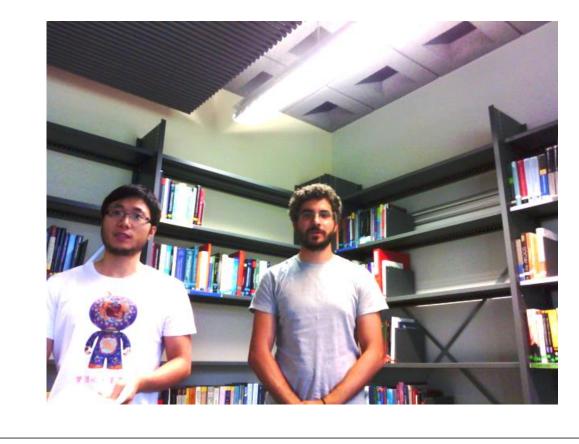
### Data:

- 24 hours of real recordings of Pepper.
- Up to two simultaneous speakers.

## Loudspeakers (16h train / 8h test)



## **Human talkers** (4 min test)



# **Baseline methods:**

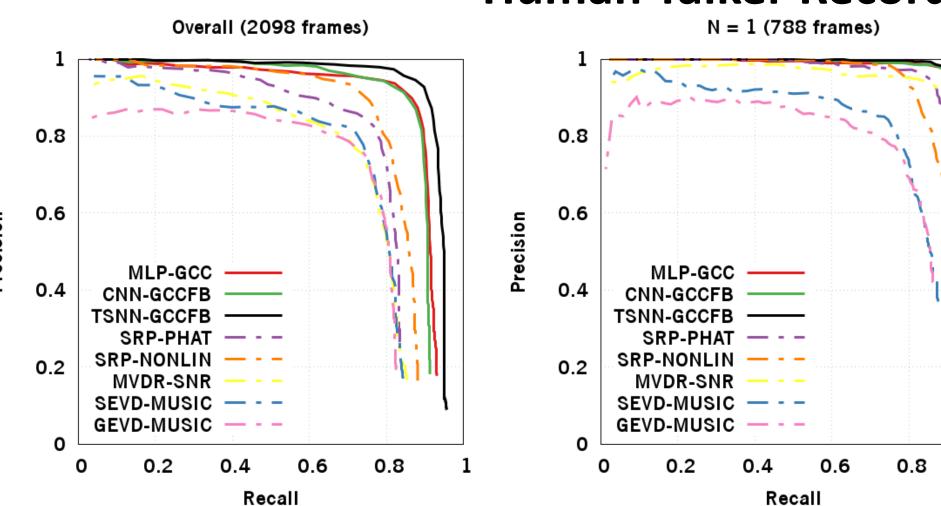
SRP-PHAT, MVDR, MUSIC

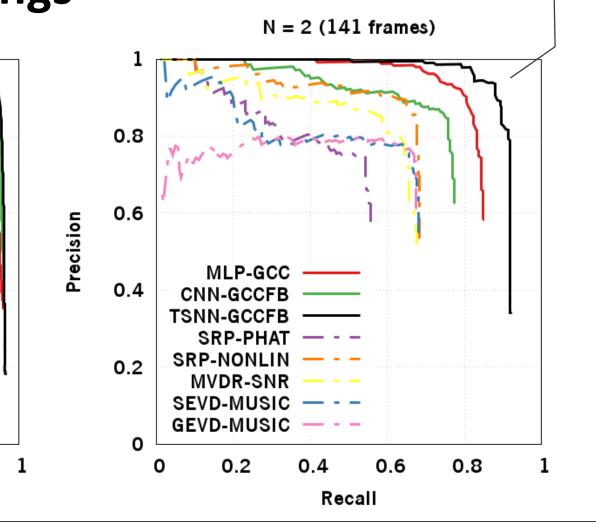
#### **Evaluation:**

- Number of sources is unknown => detection problem
- Prediction is correct if error < 5°
- Compute precision vs recall

>90% recall and precision.

## **Results:** Loudspeaker Recordings Overall (261k frames) N = 1 (178k frames) N = 2 (29k frames) 1. Proposed methods have 2. More significant with 3. Two-stage network better overall performance performs the best overlapping sources **Human Talker Recordings**





## Conclusion

Significantly better than popular spatial spectrum methods.

## Resources

- https://www.idiap.ch/dataset/sslr Database:
- https://youtu.be/ 4EwuVIE pU Video:

