INTERNATIONAL AUDIO LABORATORIES ERLANGEN
A joint institution of Fraunhofer IIS and Universität Erlangen-Nürnberg

AUDIO LABS

Broadband DOA Estimation using Convolutional Neural Networks Trained with Noise Signals

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FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

Fraunhofer IIS

Motivation
Signal processing methods

- Cross-correlation-based methods
  - GCC-PHAT
  - SRP-PHAT
  - MCCC…
- Subspace-based methods
  - MUSIC...
- Model-based methods
  - Maximum-likelihood estimation...
- ...

Challenges

- Performance degradation in presence of noise and reverberation
- High computational cost

Motivation
Supervised learning methods

- Advantage: Supervised learning methods can be adapted to different acoustic environments

- Recently, deep neural network (DNN) based supervised learning methods have been successful across a range of applications:
  - Automatic speech recognition
  - Object recognition in images
  - Machine translation….

- Few DNN based methods that estimate DOA of a sound source from the observed signals

[1] Xiao et al. "A learning-based approach to direction of arrival estimation in noisy and reverberant environments,“ 2015
[2] Takeda et al. "Sound source localization based on deep neural networks with directional activate function exploiting phase information“ 2016

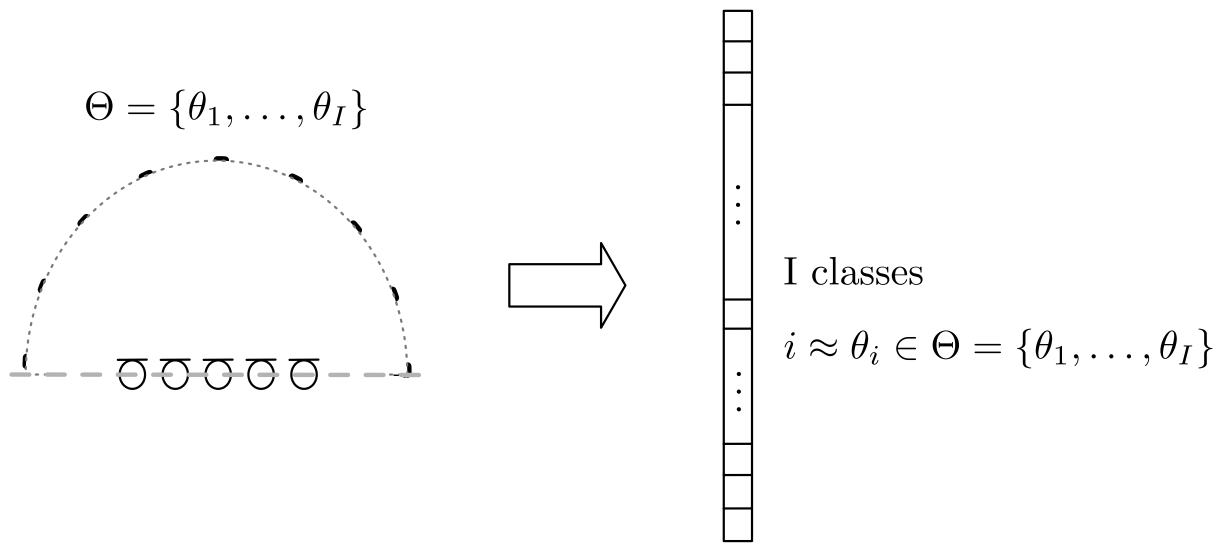
Motivation
DNN based DOA estimation

Aim: A DNN based supervised learning method for DOA estimation that

- Estimates DOA per time frame given the STFT representation of the observed signals
- Simple input representation to learn relevant features during training

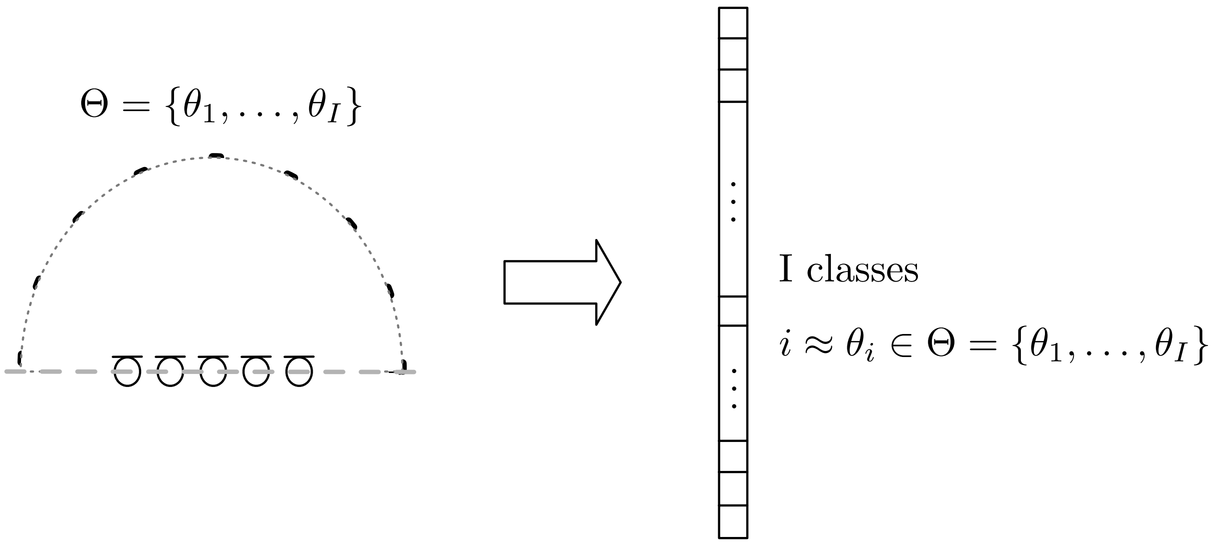
Problem Formulation

DOA estimation as classification



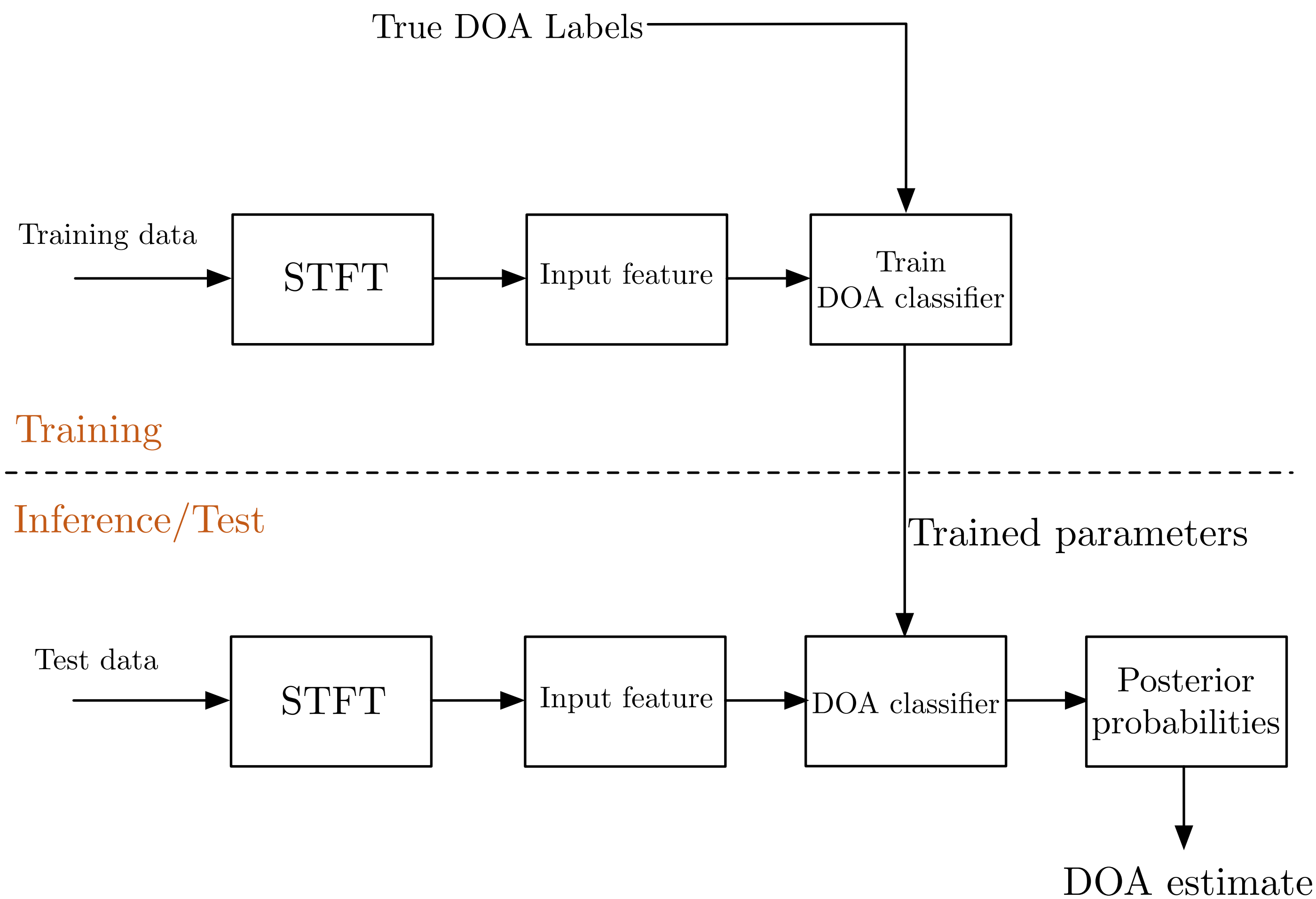
- DOA estimation is formulated as an I class classification problem
- Discretize the whole DOA range into I discrete values to obtain a set of possible DOA values: $\Theta = \{\theta_1, \ldots, \theta_I\}$
- Each class corresponds to a possible DOA value in the set

Problem Formulation
DOA estimation as classification



- For each frame, compute the posterior probability for each class
- DOA estimate is the DOA of the class with the highest posterior

System Overview
Supervised learning framework



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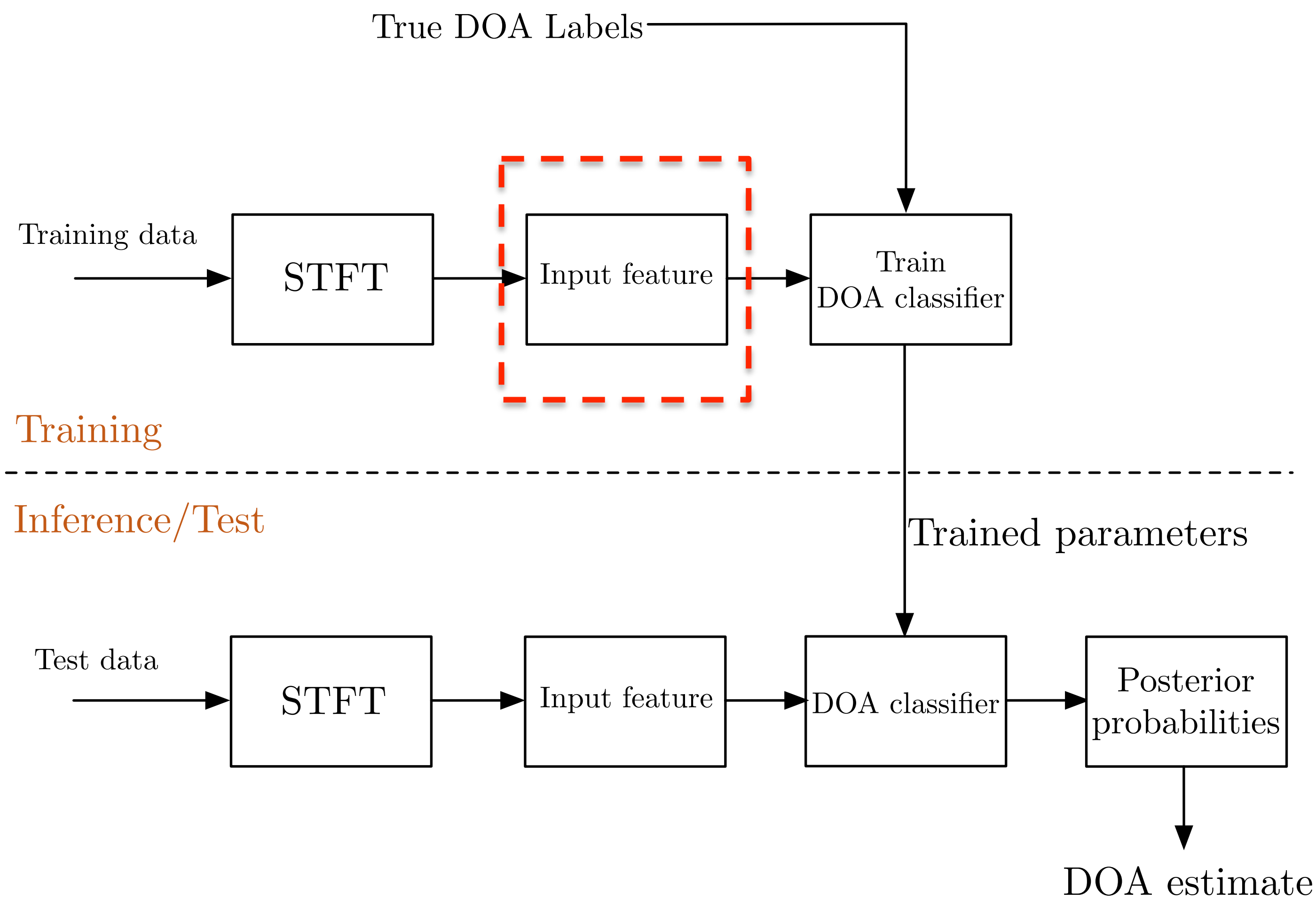
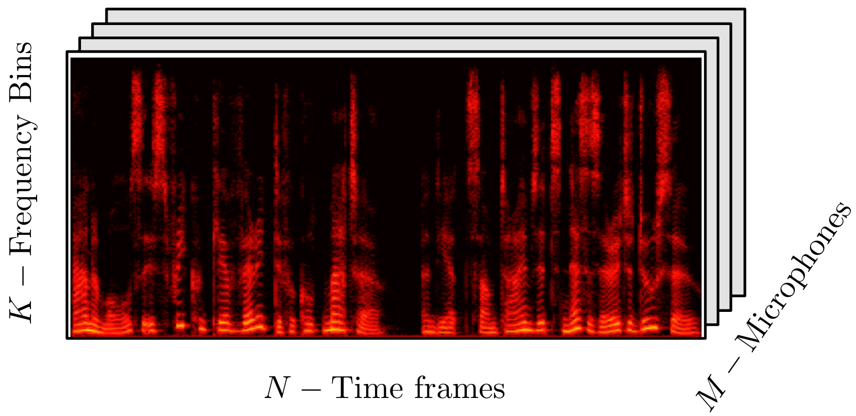
Supervised learning framework



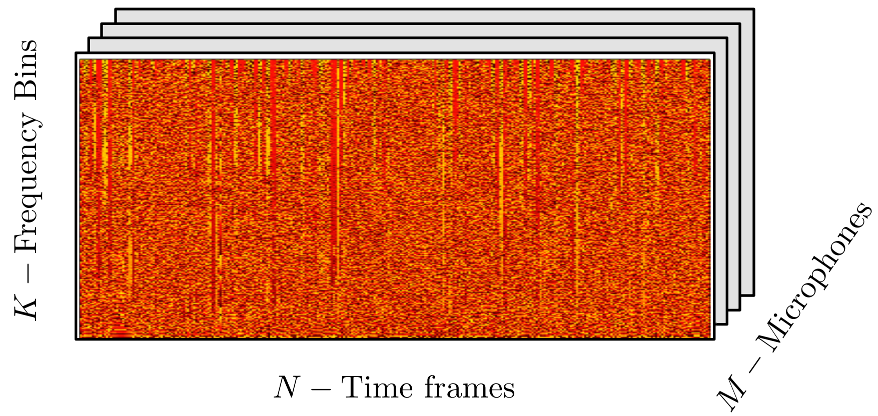
Input feature representation

STFT magnitude and phase component

$$Y_m(n,k) = A_m(n,k)e^{j\phi_m(n,k)}$$



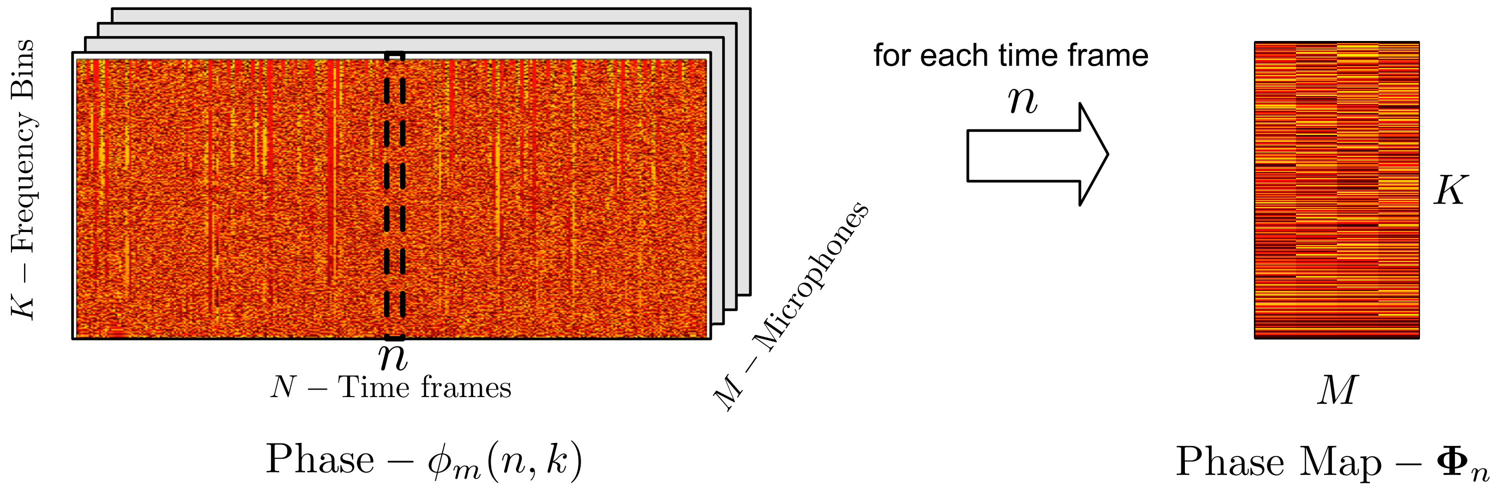
Magnitude – $A_m(n,k)$



Phase – $\phi_m(n,k)$

Input feature representation

Phase map



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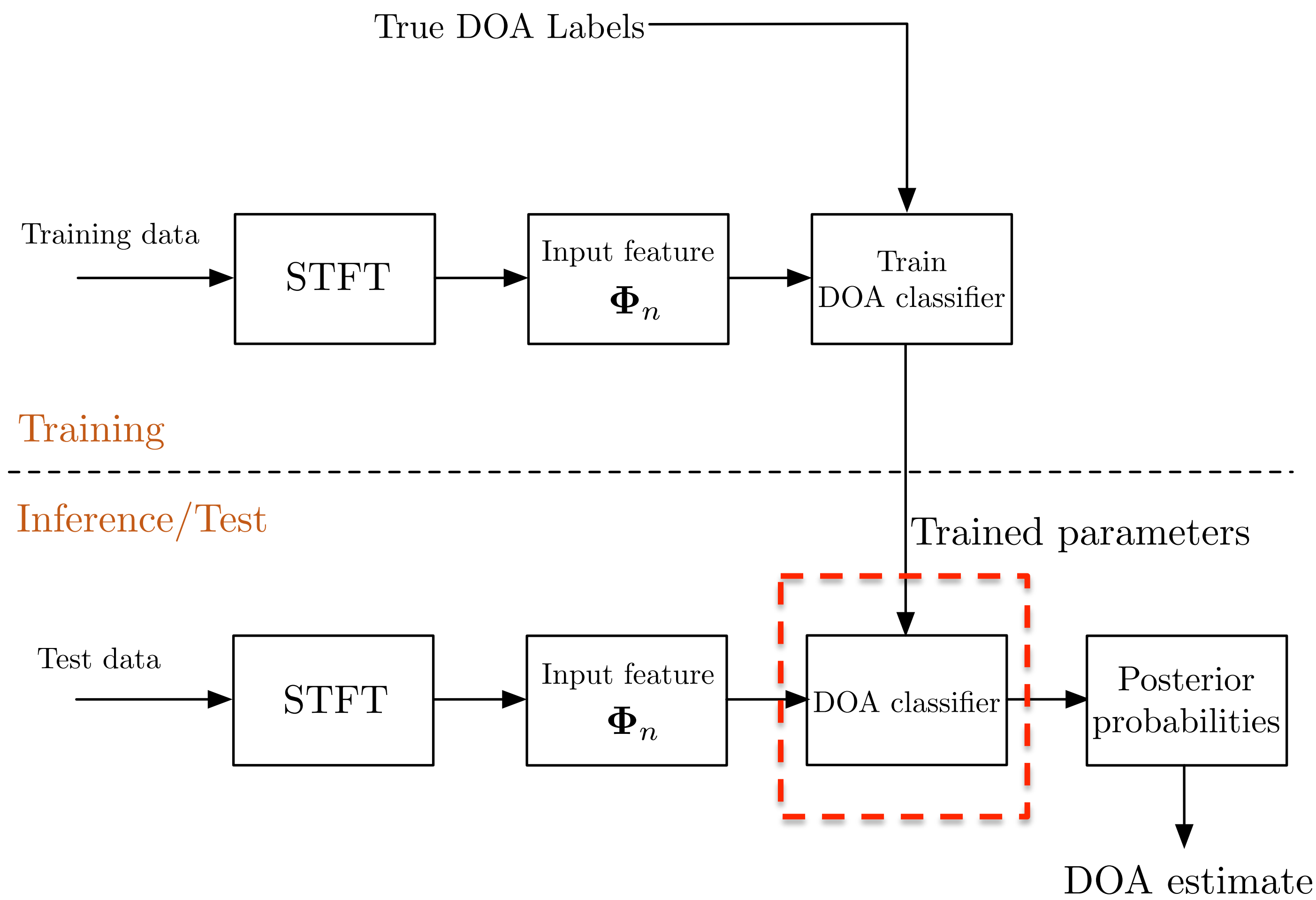
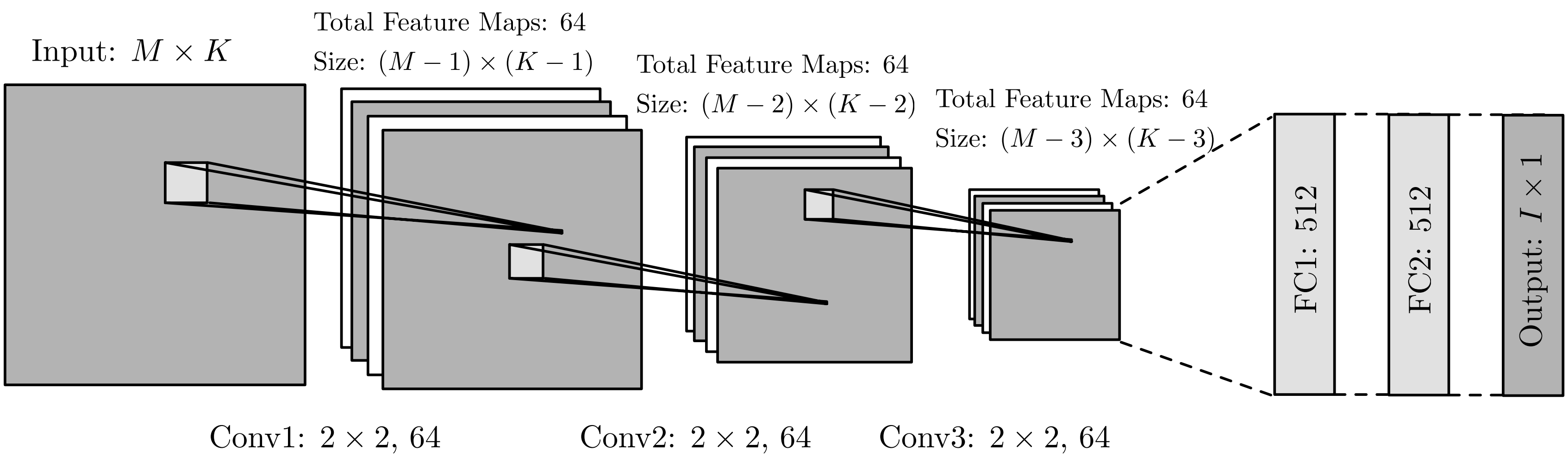
Supervised learning framework



CNN Architecture

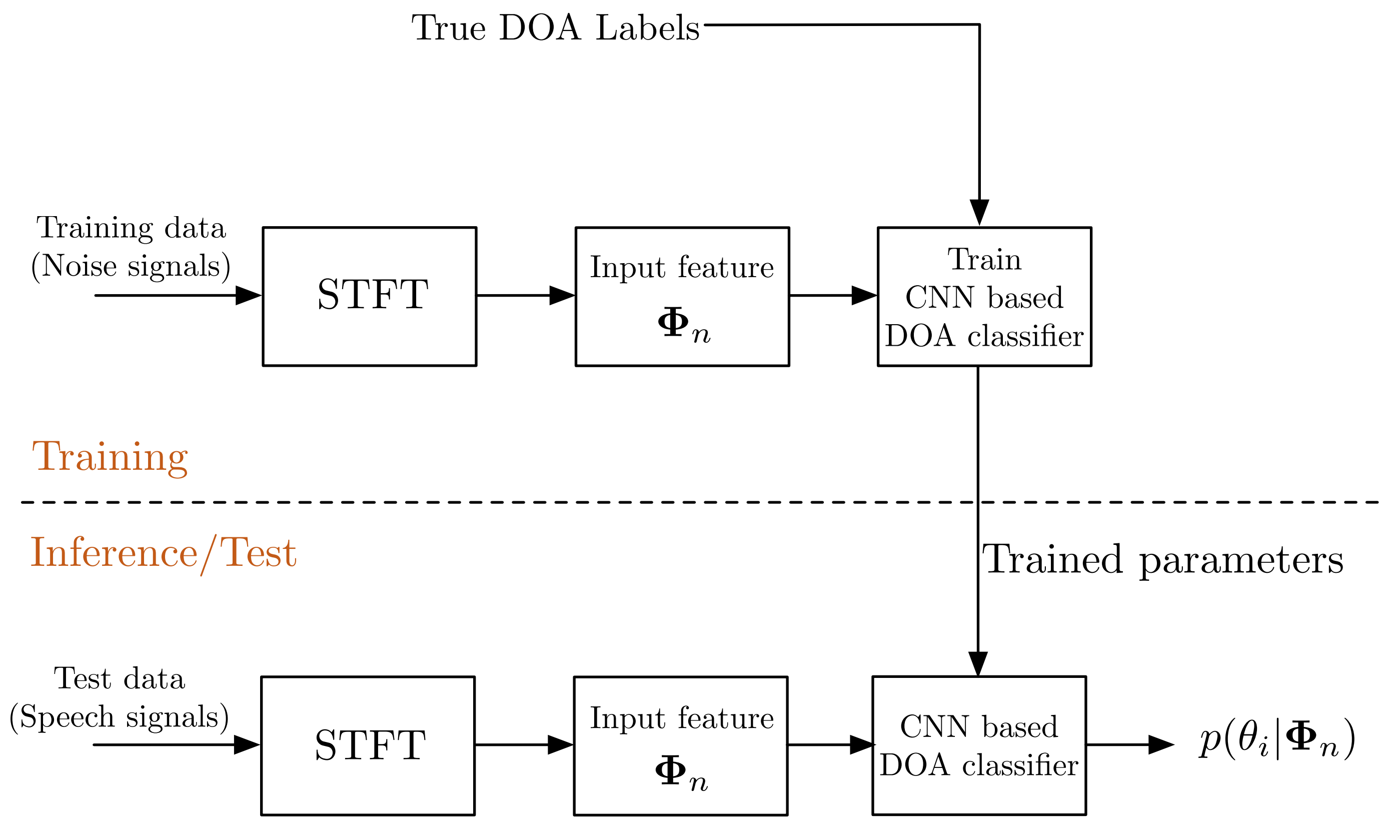


- Pooling is not employed
- Experiments showed decreased performance

Training with synthesized noise signals

- CNN learns the required information for DOA estimation from the phase map
- CNN can be trained using synthesized noise signals (!?)
- Advantages:
  1. No speech/audio database required
  2. Easier to create training data
- Spectrally white noise was used

System overview



DOA estimate

$$\hat{\theta}_n = \underset{\theta_i}{\arg\max}\ p(\theta_i|\mathbf{\Phi}_n)$$

Evaluation
Experiments

1. Generalization to speech and robustness to noise
2. Performance in acoustic conditions different from training
3. Robustness to small perturbations in microphone positions
4. Real acoustic environments

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Evaluation
Performance measure

- Performance of CNN compared to SRP-PHAT
- Evaluation measure
  - Frame-level accuracy

$$A(\%) = \frac{\hat{N}_c}{N_s} \times 100,$$

$$N_s - \text{Total time frames with speech active}$$

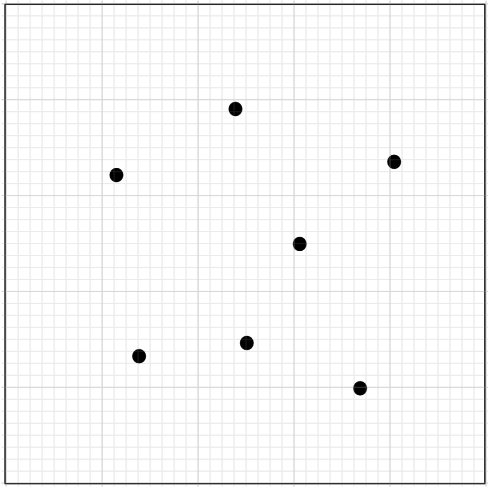
$$\hat{N}_c - \text{Time frames with correct estimate}$$

Evaluation
Experimental parameters

- Uniform linear array (ULA)
  - Number of microphones = 4
  - Inter-microphone distance = 3 cm
- STFT length 256, 50% overlap
- Resolution for classes: 5 degrees, I = 37 classes
- Training data is simulated using RIR generator [3]

[3] https://github.com/ehabets/RIR-Generator

Evaluation
CNN training conditions



Room with training positions

Simulated training data	
Signal	Synthesized noise signals
Room size	R1: (6×6) m , R2: (5×5) m
Array positions in room	7 different positions in each room
Source-array distance	1 m and 2 m for position
RT_{60}	R1: 0.3 s, R2: 0.2 s
SNR	Uniformly sampled from 0 to 20 dB

Evaluation

CNN training parameters

- **Training data**: 5.6 million time frames
- **Validation data**: 20% split from the training data
- **Loss**: Cross-entropy
- **Activation**: ReLU, Softmax (final layer)
- **Optimizer**: Adam
- **Batchsize**: 512
- **Nb Epochs**: 10
- **Regularization**: Dropout rate 0.5 (After Conv.3 layer, and each FC layer)

Evaluation
Test conditions

- **Database**: TIMIT test
- **Speech samples**: 500, 4 s each
- **Test data size**: 100000 active time frames

Simulated test data	
Signal	Speech signals from TIMIT
Room size	Room 1: (7×6) m , Room 2: (8×8) m
Array positions in room	1 random position for each room
Source-array distance	1.5 m for both rooms
RT_{60}	Room 1: 0.45 s, Room 2: 0.53 s
SNR	2 categories: 5 dB, and 15 dB

Evaluation

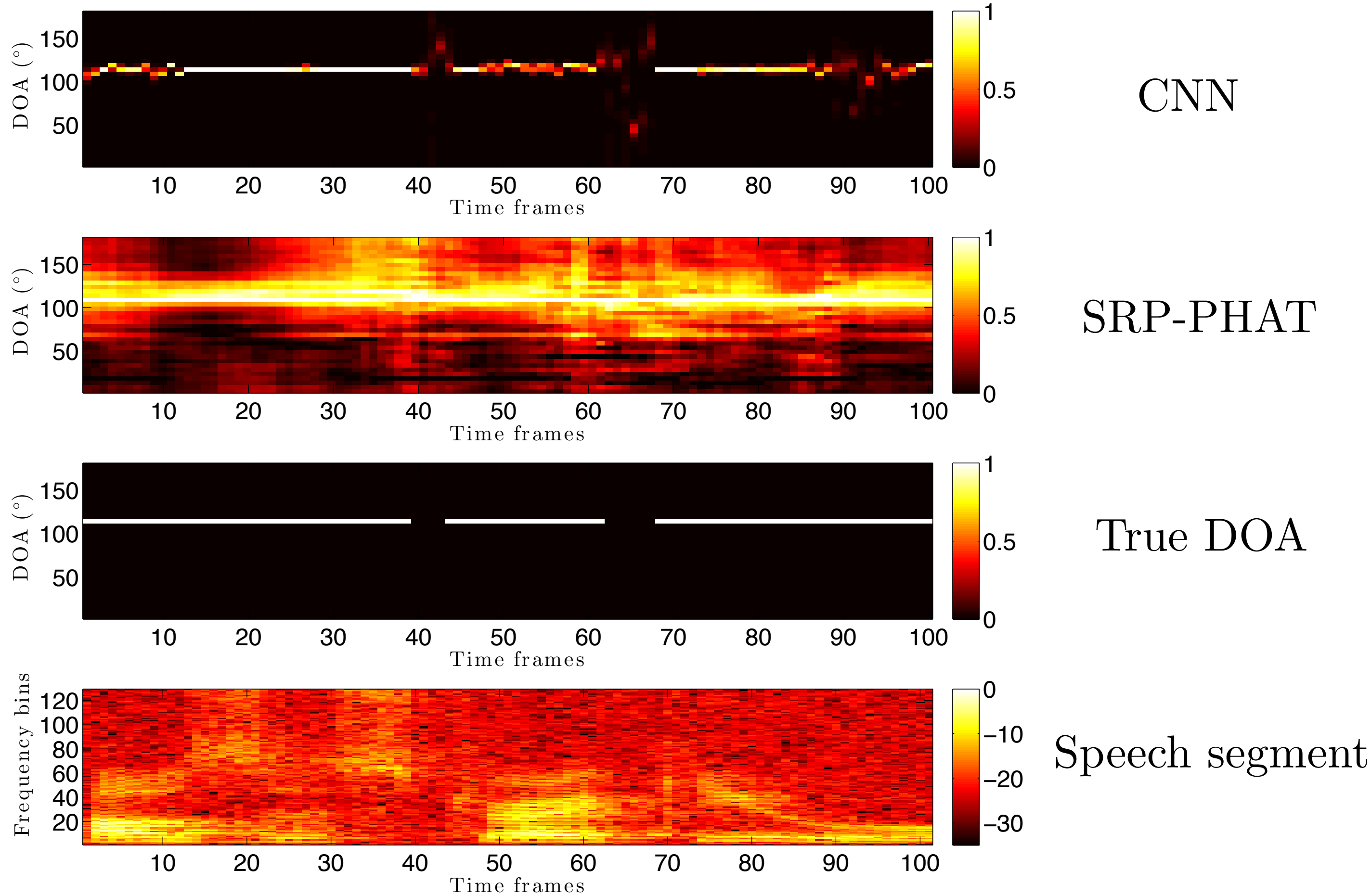
Test conditions

Frame-level accuracies (%)

	Room 1		Room 2	
	5 dB	15 dB	5 dB	15 dB
CNN	56.2	69.8	54.1	68.2
SRP-PHAT	22.6	33.6	21.8	38.4

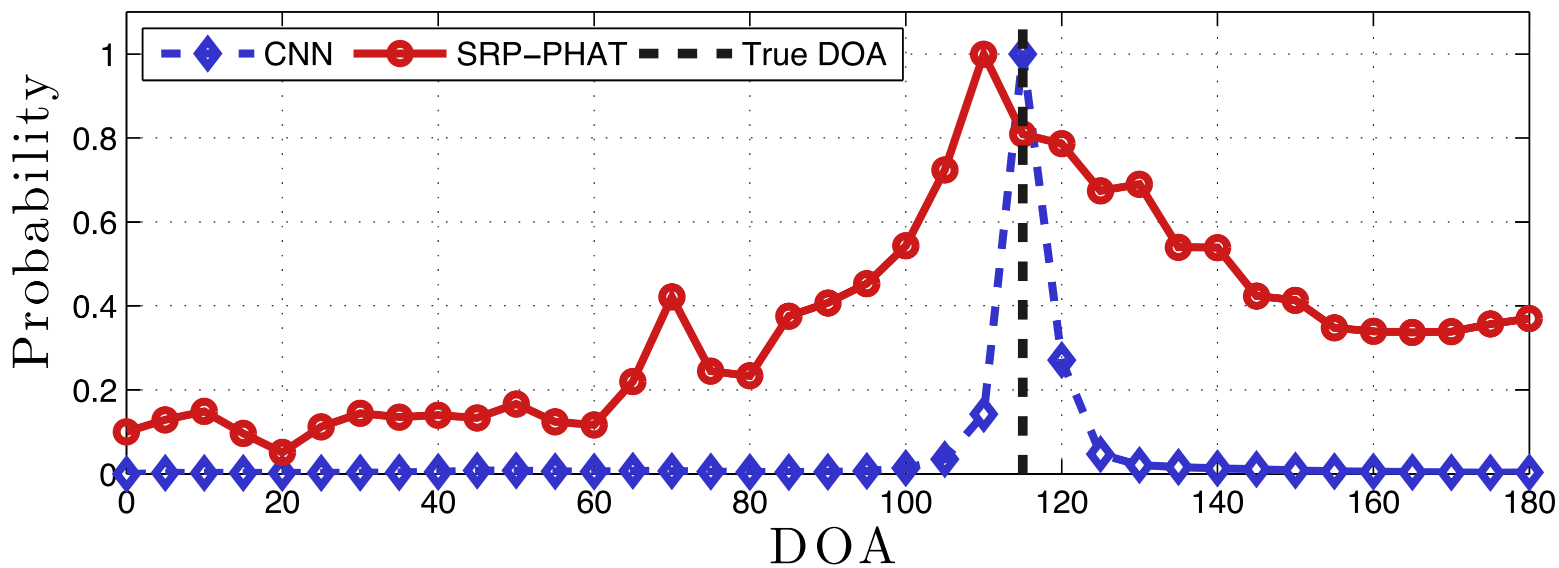
- Better performance compared to SRP-PHAT
- For all cases, CNN is accurate for the majority of the frames

Evaluation
Qualitative results - Room 2, 15 dB



Evaluation

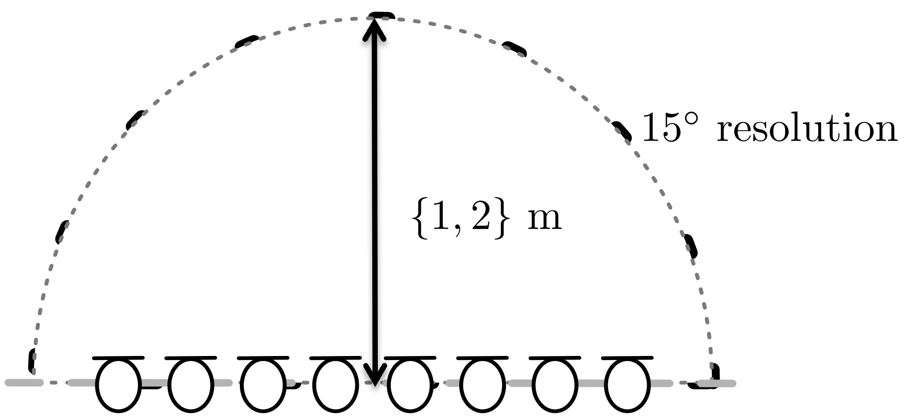
Qualitative results – Average over 0.8 s



Evaluation

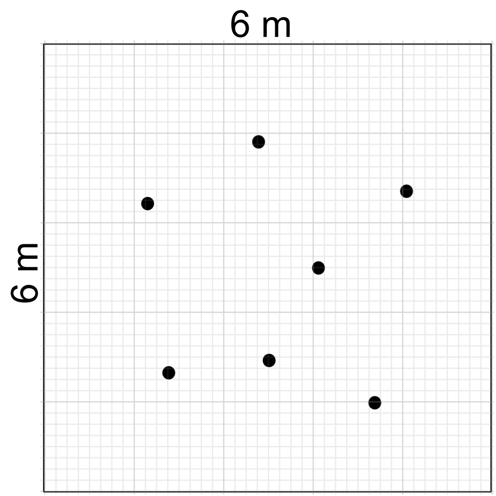
Real environment – Measured RIRs

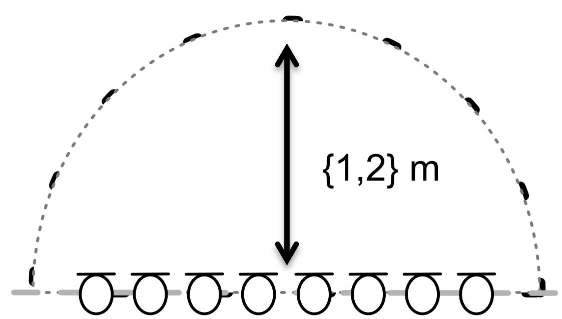
- **Database**: Multichannel Impulse Response Database from Bar-Ilan
- **Source setup**: $[0^\circ, 180^\circ]$, steps of 15 degrees
- **Array configuration**: M = 8 microphones, d = 8 cm
- **Source-array distances**: 1 m and 2 m
- **Test sample**: 15 s long speech sample



Evaluation
Real environment – Measured RIRs

- **Database**: Multichannel Impulse Response Database from Bar-Ilan
- **Source setup**: $[0^\circ, 180^\circ]$, steps of 15 degrees
- **Array configuration**: [8,8,8,8,8,8,8], M = 8 microphones
- **Source-array distances**: 1 m and 2 m
- **Test sample**: 15 s long speech sample
- CNN was retrained for the new array geometry (with simulated data)





Evaluation
Real environment – Measured RIRs

Frame-level accuracies (%)

	$RT_{60} = 0.160$ s		$RT_{60} = 0.360$ s		$RT_{60} = 0.610$ s	
	1 m	2 m	1 m	2 m	1 m	2 m
CNN	91.8	88.7	86.8	79.4	72.3	67.3
SRP-PHAT	94.4	69.0	87.1	68.3	71.7	62.4

- For 2 m distance, CNN outperforms SRP-PHAT
- SRP-PHAT performs better at lower reverberation times for 1 m source-array distance

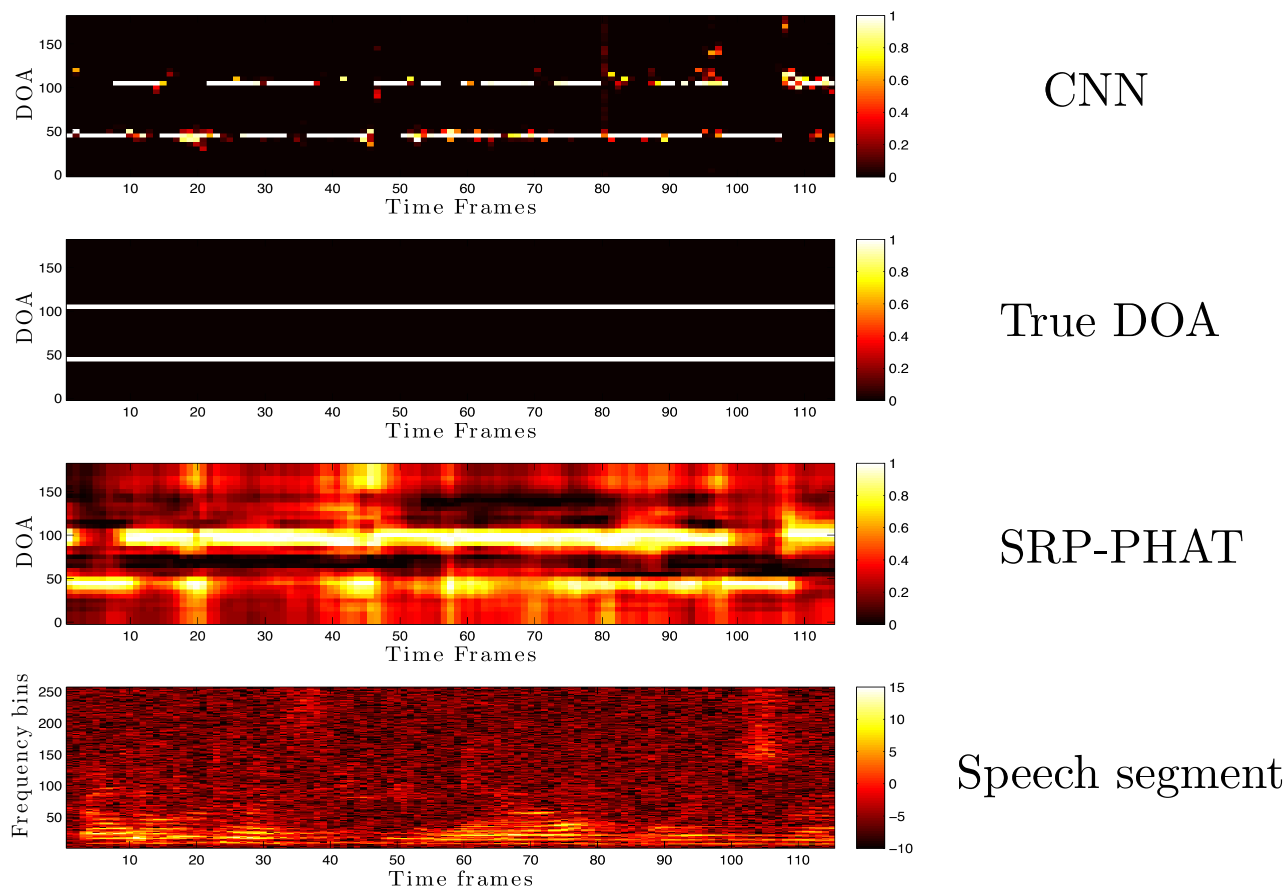
Conclusions

- Proposed a CNN based supervised learning method for DOA estimation with a simple input representation
- CNN trained with synthesized noise signals is able to localize a speech source
- Proposed system performs better than SRP-PHAT in unmatched simulated acoustic conditions
- Adaptability to unseen real acoustic environments was also demonstrated

Current Work
Multi-speaker localization

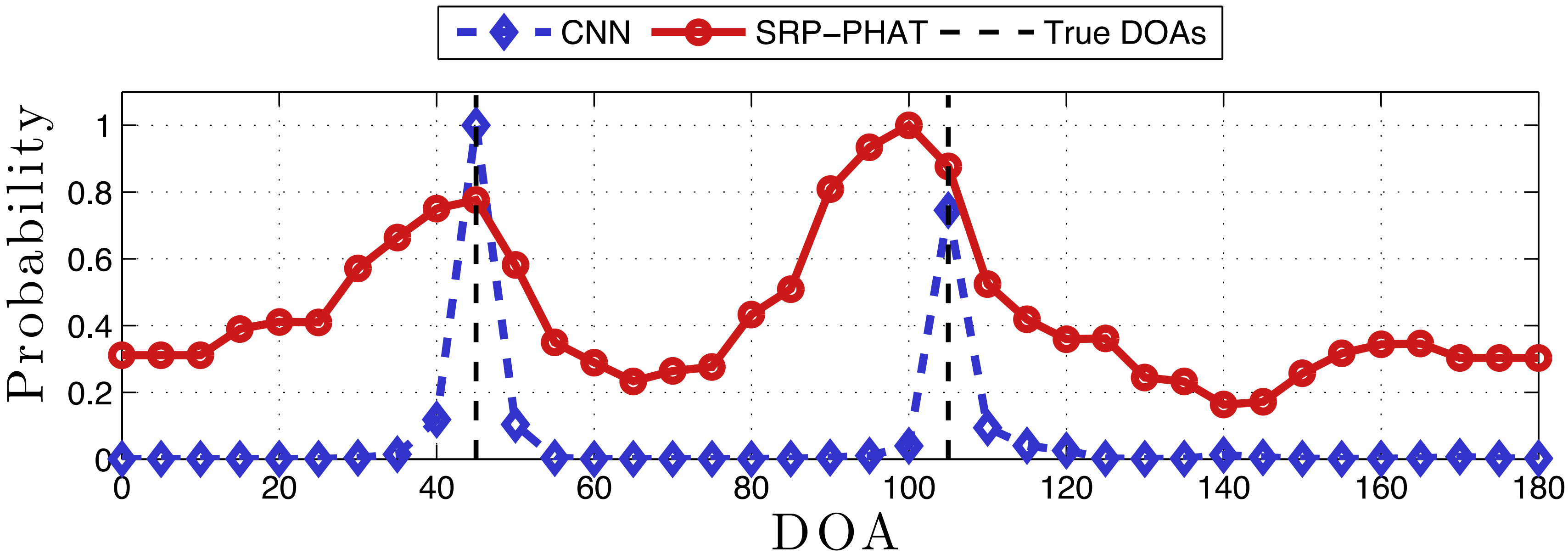
- Aim: Localize simultaneously active speakers
- Formulate multi-speaker localization as a multi-class multi-label classification problem

Current Work
Multi-speaker localization



Current Work

Multi-speaker localization



Still trained with synthesized noise signals!!

Thank you for your attention!

Trained model and weights available:

Soumitro-Chakrabarty/Single-speaker-localization