Matched-field source localization using sparsely-coded neural network and data-model mixed training

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MFP and SSP mismatch problem

- Source localization is a basic problem in underwater acoustics
  - matched-field processing (MFP) is one of the mostly-studied;
  - sensitive to the mismatch problem;
- Machine learning methods learn directly from the observation
  - do not require a good *a prior* information;
  - can be designed to implement a required processing;
  - be able to work at different scenarios by well trained;
- View source localization as a machine learning problem
  - easy to establish a probability distribution model by neural networks;
  - also, capable of representing almost any data distribution;
  - convenient for us to train the model by using modern machine learning frameworks.

Contents

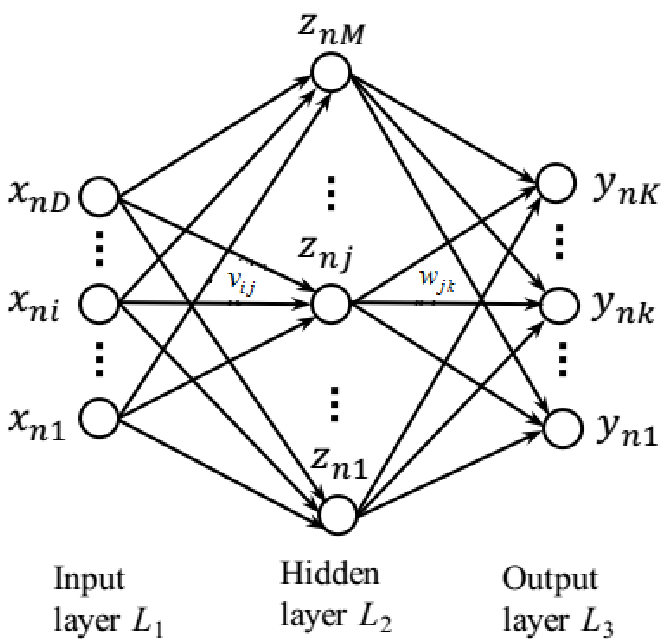
- Neural network based source localization prediction model
- Performance comparison with two MFP methods
- Model robustness on SSP mismatch
- Data-model mixed training
- Summary & Future work

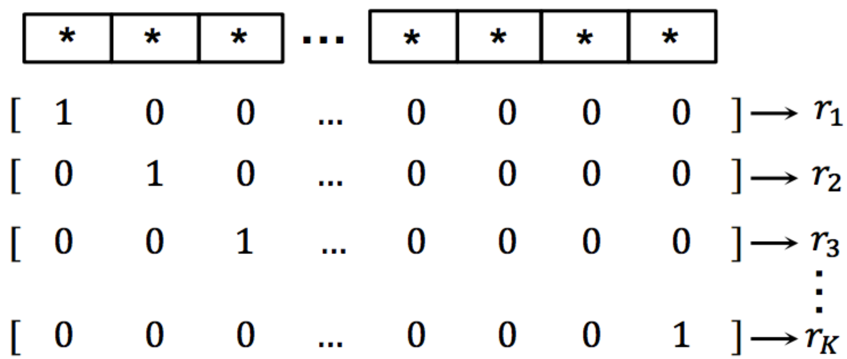
Neural network based source localization

Input: Sample cov. Matrix: 441 Neurons (21*22/2*2-21) per frequency

Output: binary range vector: 1.1475-8.6475 km, 300 neurons, 25m each

Just one middle layer, 500 Neurons

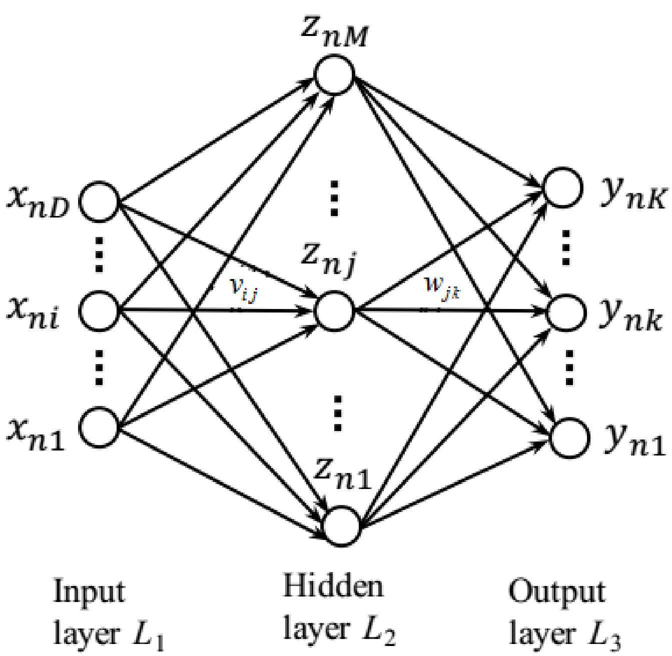




[1] Niu, H., and Gerstoft, P. Source localization in an ocean waveguide using supervised machine learning. JASA (2017), 1176–1188.

Neural network based source localization

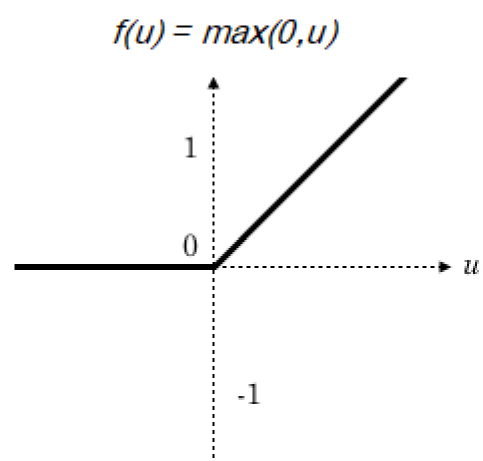
- FNN with one hidden layer



(a)

$$\boldsymbol{z} = f(\mathbf{V}\boldsymbol{x} + \boldsymbol{b}_1)$$

$$\boldsymbol{y} = h(\mathbf{W}\boldsymbol{z} + \boldsymbol{b}_2)$$



h: *softmax function*

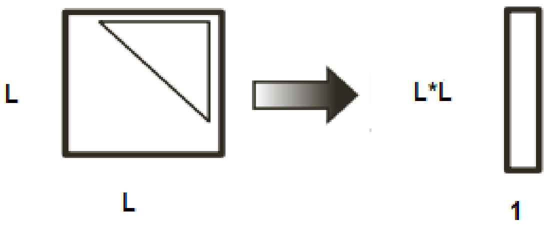
$$a = \mathbf{W}z + b_2$$

$$y_k = \frac{e^{a_k}}{\sum_{j=1}^{K} e^{a_j}}$$

(b)

Neural network based source localization

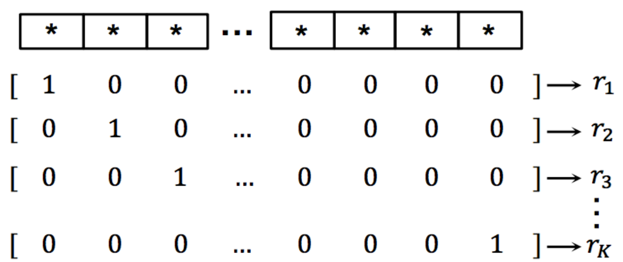
- Input data preprocessing
  - Sound pressure: $$\boldsymbol{p}(f) = S(f)\boldsymbol{g}(f, r) + \boldsymbol{n}$$
  - Normalized: $$\tilde{\boldsymbol{p}}(f) = \frac{\boldsymbol{p}(f)}{\|\boldsymbol{p}(f)\|_2}$$
  - Sample covariance matrices: $$\boldsymbol{C}(f) = \frac{1}{N_s}\sum_{s=1}^{N_s} \tilde{\boldsymbol{p}}_s(f)\tilde{\boldsymbol{p}}_s^H(f)$$
  - Concatenate upper triangular elements' real and imaginary parts, vectorize to create input x



Neural network based source localization

- Source range mapping
  - Mapping rang into K bins of width with Δr

$$t_{nk} = \begin{cases} 1 & if \left\| r - r_k \right\| \le \dfrac{\Delta r}{2} \\ 0 & otherwise \end{cases}$$



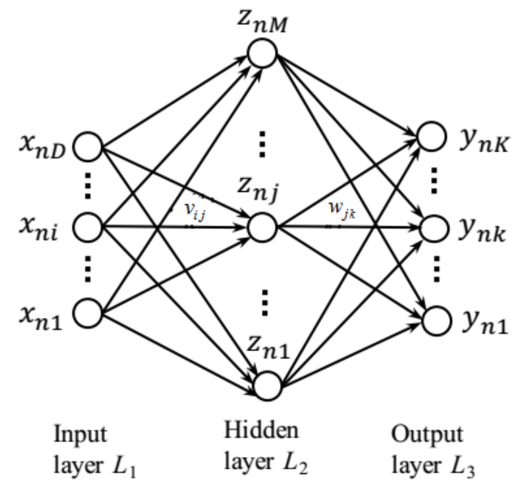
- Training criterion
  - negative log-likelihood & sparsity constraint on FNN

$$E(\mathrm{w}) = -\frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K} t_{nk} \ln y_{nk} + \lambda_1 \left\| z \right\|_1 + \lambda_2 \left\| V \right\|_{2,1}$$

- Definition of model accuracy

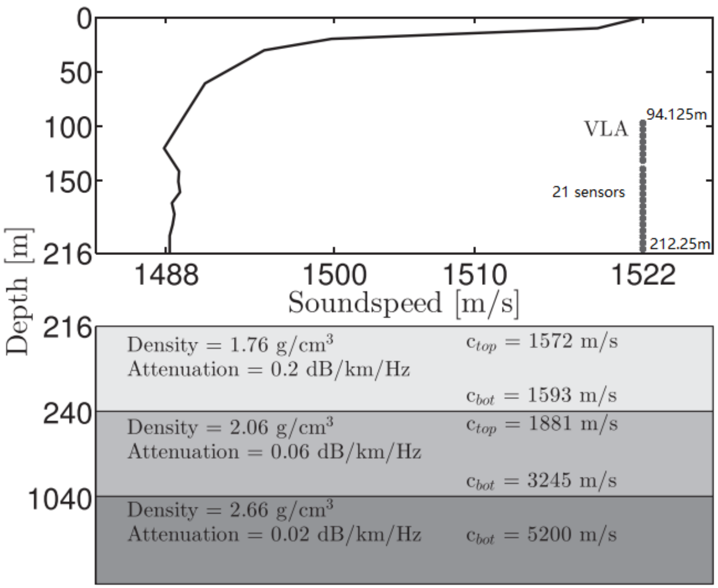
$$acc = \frac{1}{N}\sum_{n=1}^{N} I(y_n, t_n) \times 100\%$$

$$I(y_n, t_n) = \begin{cases} 1 & \text{if } y_n = t_n, \\ 0 & \text{otherwise.} \end{cases}$$

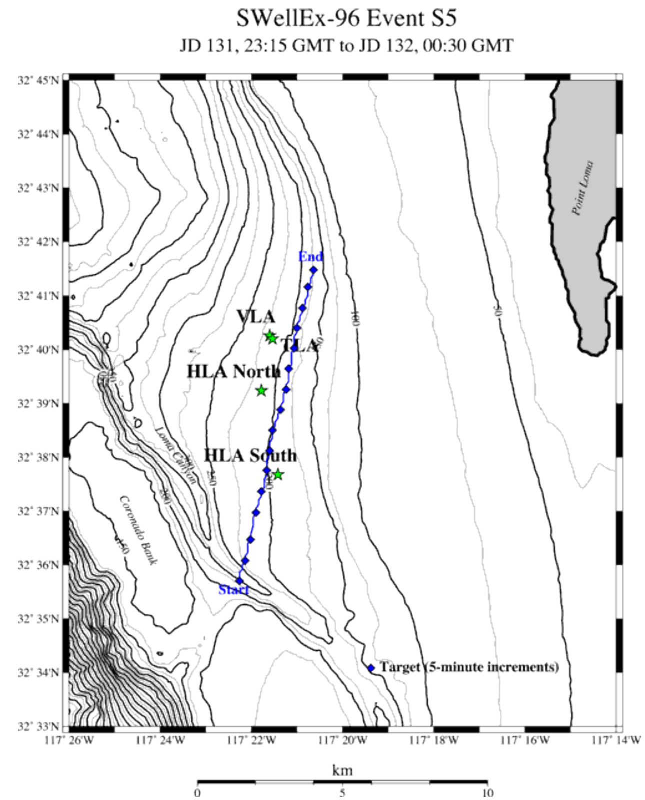


SWellEx96 Event S5

- Environmental model and source-receiver configuration
  - Shallow source: depth 9m;
  - Frequency: 109, 232, 385Hz used;



(a)



(b)

Performance comparison with MFP

- SWell96Ex-S5 experimental data
  - Accuracy: SCFNN > MCE > Bartlett1 > Bartlett2

Table 1: Localization accuracy of SCFNN and MFP

Methods	SCFNN	MCE	Bartlett 1	Bartlett 2
109Hz	89.3%	72.3%	37.7%	3.7%
232Hz	97%	91%	17.7%	4.3%
385Hz	99.7%	97.7%	14%	0.67%
109,232,385Hz	99%	99.7%	40.7%	7.7%

Note: There are two kinds of replica-field used.

Bartlett 1 measurement data; Bartlett 2, simulated by model.

Performance comparison with MFP

- SWell96Ex-S5 experimental data
  - Error: SCFNN < MCE < Bartlett1 < Bartlett2

Table 2: Absolute mean error of SCFNN and MFP

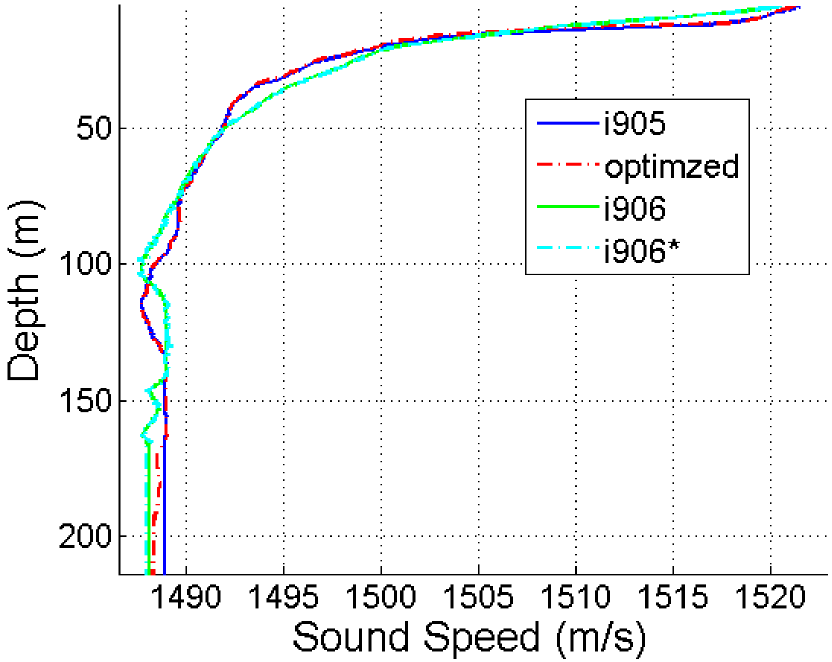
Methods	SCFNN	MCE	Bartlett 1	Bartlett 2
109Hz	28.1	290.3	852.8	1219.5
232Hz	7.4	2.5	832.3	832.3
385Hz	0.08	0.58	1266.7	1756.3
109,232,385Hz	0.25	0.083	477.2	722.9

Note: There are two kinds of replica-field used.

Bartlett 1 measurement data; Bartlett 2, simulated by model.

Model robustness on SSP mismatch

- Different degrees of error in the knowledge of SSP



Compared to the optimized,

a) i906, significant change in shape ;

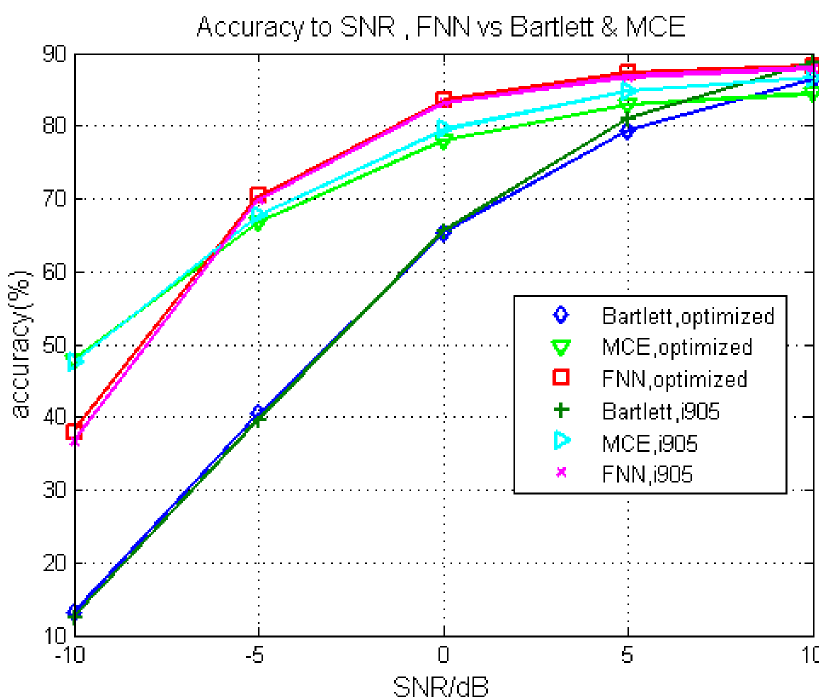
b) i905, change is slight;

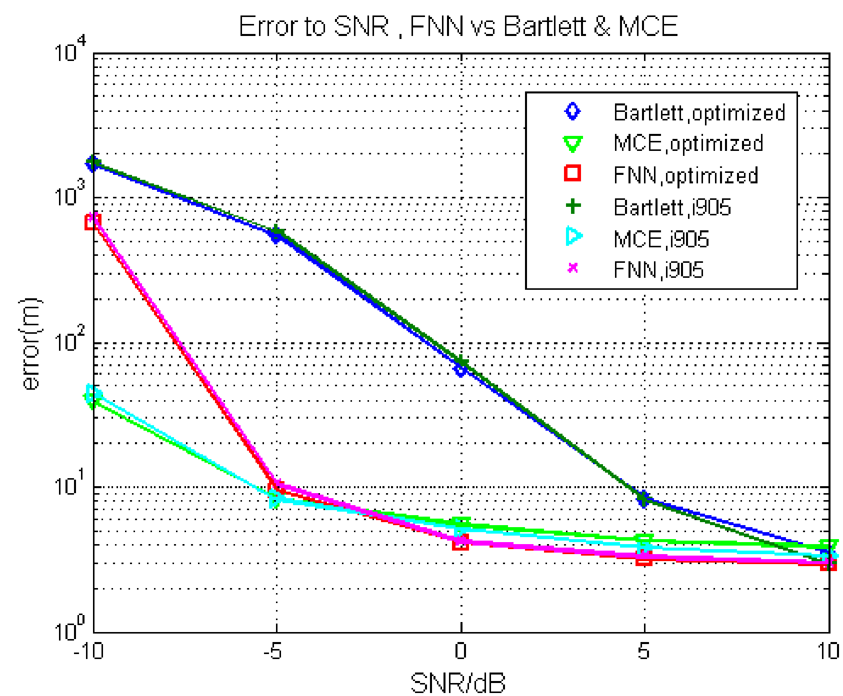
c) i906*, changed from i906, for the sake of testing.

- optimized one is the best SSP model for real environment of SWellEx-96 experiment, while,i906, i905 are the measured SSPs from different stations.

Model robustness on SSP mismatch

- Monte-Carlo Simulation (1000 times)
  - Case 1: light change in SSP

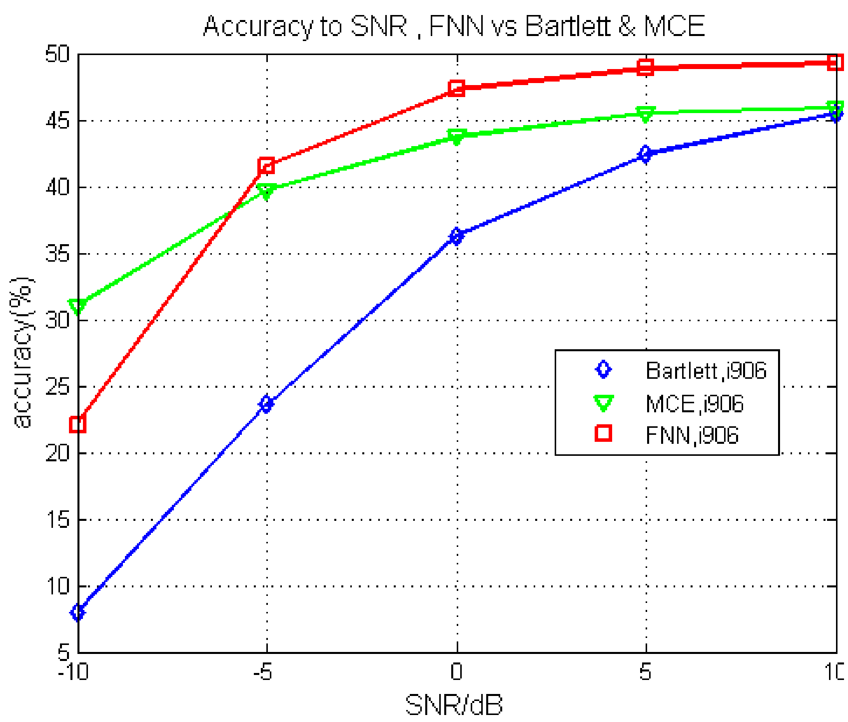


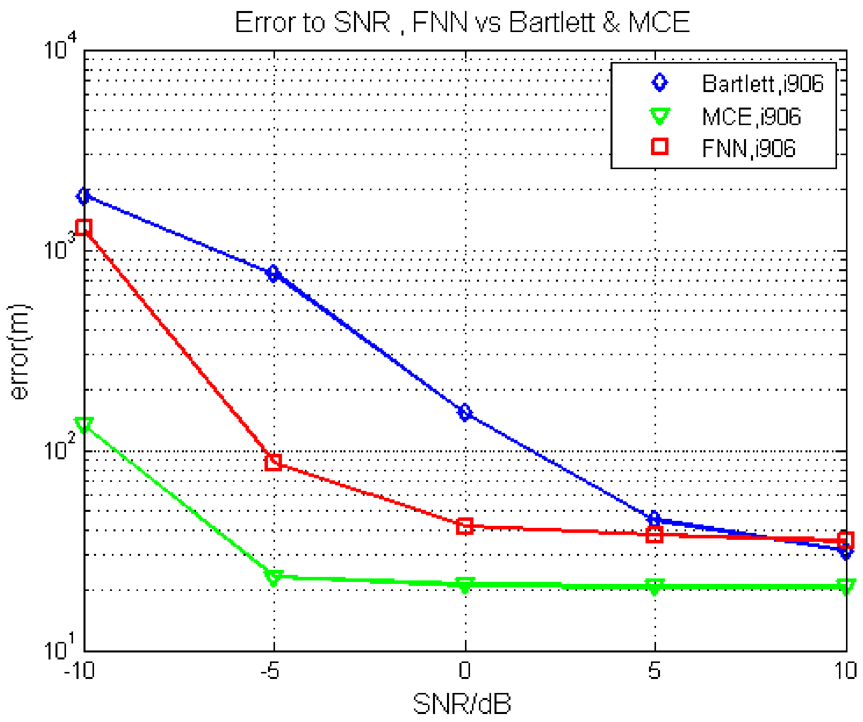


SCFNN positions best, followed by MCE and Bartlett worst;

Model robustness on SSP mismatch

- Monte-Carlo Simulation (1000 times)
  - Case 2: large change in SSP



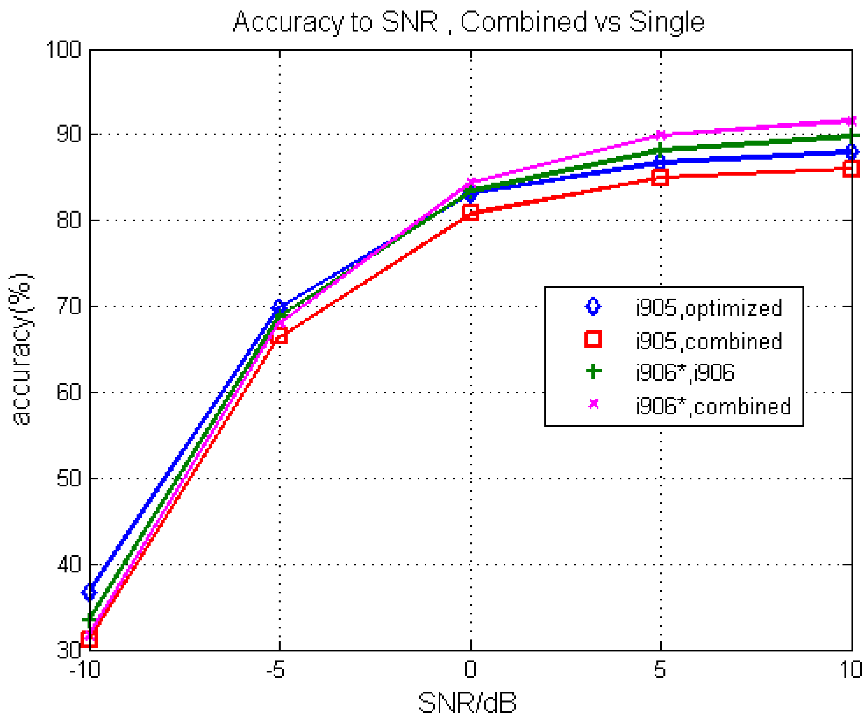


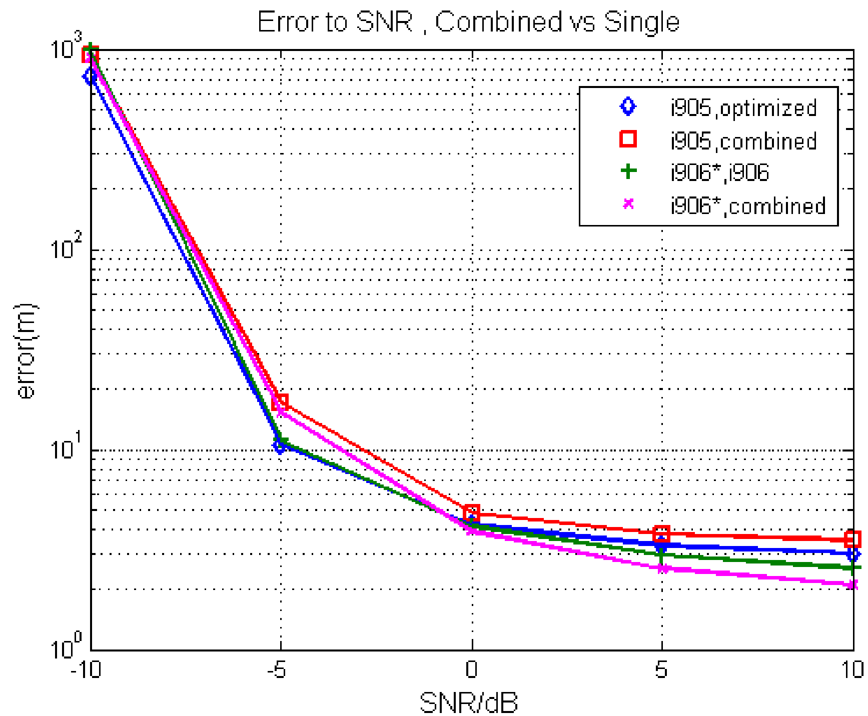
accuracy order unchanged;

absolute mean error, SCFNN larger than MCE.

Data-model mixed training

- Monte-Carlo Simulation (1000 times)
  - Model robustness is significantly improved





Summary

- SCFNN works well in localization problem
  - perform better than Bartlett, MCE methods;
- and is also sensitive to SSP mismatch
  - varying on different degrees of error in the knowledge of SSP;
  - still performs better than Bartlett and close to the MCE method;
- model robustness can be improved by data-model mixed training
  - SCFNN classifier can work well on two entirely different SSPs;
  - performance may be improved by add some ‘noise’ data;
  - also, neural network based model behaves poorly in low SNR case.

Future work

- Feature enhancement & adversarial learning on noise;
- Mathematical analysis & explain robustness on mixed training.

Thank you for listening!

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