Beamforming with Neural Network

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04/17/2013

Outline

- Introduction
- Phased Array Theory and Implementation
- Beamforming
- Signals in the far- & near-field
- Neural network
- Simulation Procedure
- Analysis of Results
- Conclusion

Purpose and approach

- To find an optimum method for spatially filtering incoming acoustic or electro magnetic signals.
- Perform simulation in MATLAB.
- Find figure of merit in the results.

Phased Array Theory

- Combining the signals from two or more transmitting or receiving elements by varying the phase shifts and amplitude between the elements.

Fig: Typical Phased Array System

Source: Square Kilometer Array, http://www.aarnet.edu.au/CaseStudy/Square-Kilometre-Array.aspx

Phased Array Implementation

- The set of transmitting or receiving elements can be aligned so as to transmit or receive signals from particular directions.

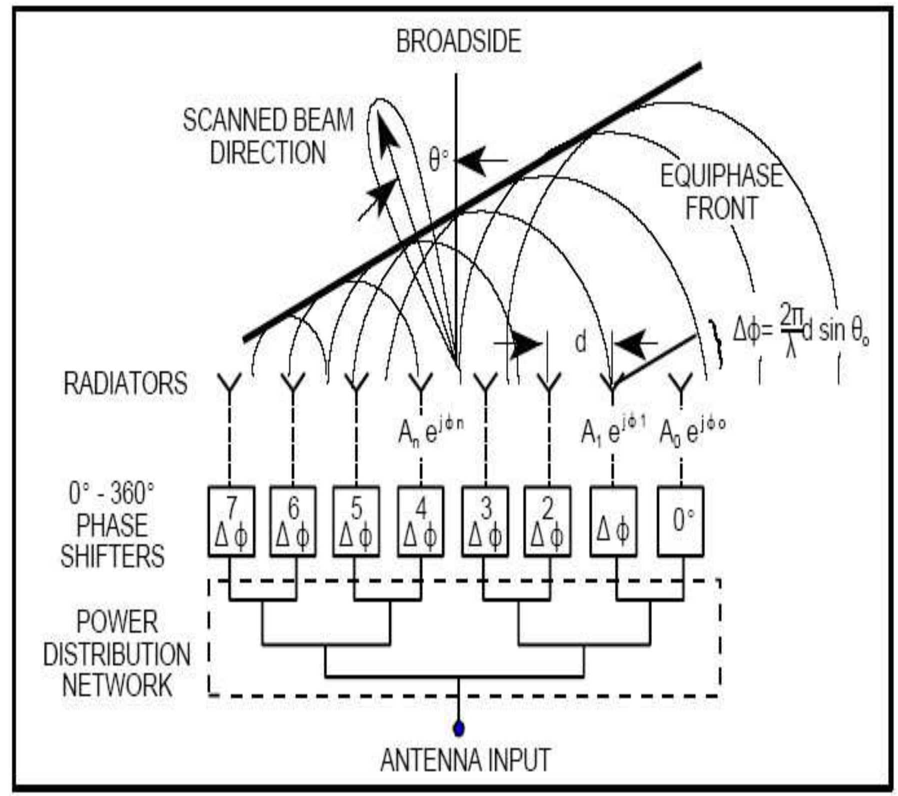


Fig: Phased Array Mechanism

Source: Phased Array Antennas, http://www.microwaves101.com/encyclopedia/phasedarrays.cfm

Working principle (1)

- General Equation for spherical signal:
  - $\vec{X}=\frac{A}{|\vec{r}|}e^{-i(\vec{k}\circ\vec{r}-\omega t)}$, $(\vec{r}=x\,\hat{x}+y\hat{y}+z\hat{z})$ and $|\vec{k}|=\frac{2\pi}{\lambda}$

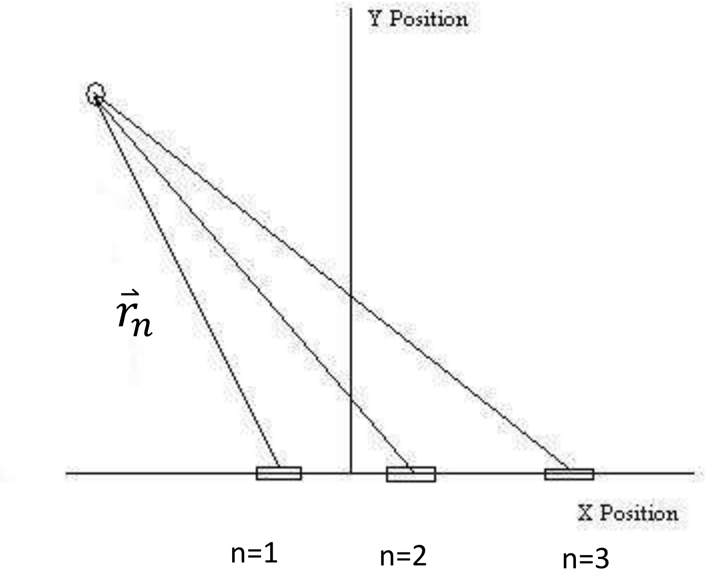


Fig: Linear Array System

Working Principle (2)

- Each array element only receives signal with value

$$X_n = \frac{A}{|\vec{r}_n|} e^{-i\frac{2\pi}{\lambda}|\vec{r}_n|}, \text{ (n=1,2,3)}$$

- So total signal received by the system is:

$$Y = \sum_{n=1}^{3} X_n = \frac{A_1}{|\vec{r}_1|} e^{-i\frac{2\pi}{\lambda}|\vec{r}_1|} + \frac{A_2}{|\vec{r}_2|} e^{-i\frac{2\pi}{\lambda}|\vec{r}_2|} + \frac{A_3}{|\vec{r}_3|} e^{-i\frac{2\pi}{\lambda}|\vec{r}_3|}$$

Beam forming

- Adjusting phased shifts and amplitudes between elements to form beams in desired directions.
- Benefits of beam forming:
  - "Steer" the array so that it is most sensitive in particular direction.
  - Cancel out interference from particular direction.
  - Provide spatial diversity reception.
  - Determine the direction of arrival.

Near- & Far-field Signals

- Reactive Near-field signals emanate from the immediate vicinity of the antenna and is the region within $r < 3\lambda$. (Non propagating waves)

- Radiative Near-field signals emanate from the region between $3\lambda < r < \frac{2D^2}{\lambda}$. (Propagating spherical waves)

- Far-field signals emanate from the distance beyond $r > \frac{2D^2}{\lambda}$ and the shape of the wave is a plane. (Propagating plane waves)

Near and Far field illustration

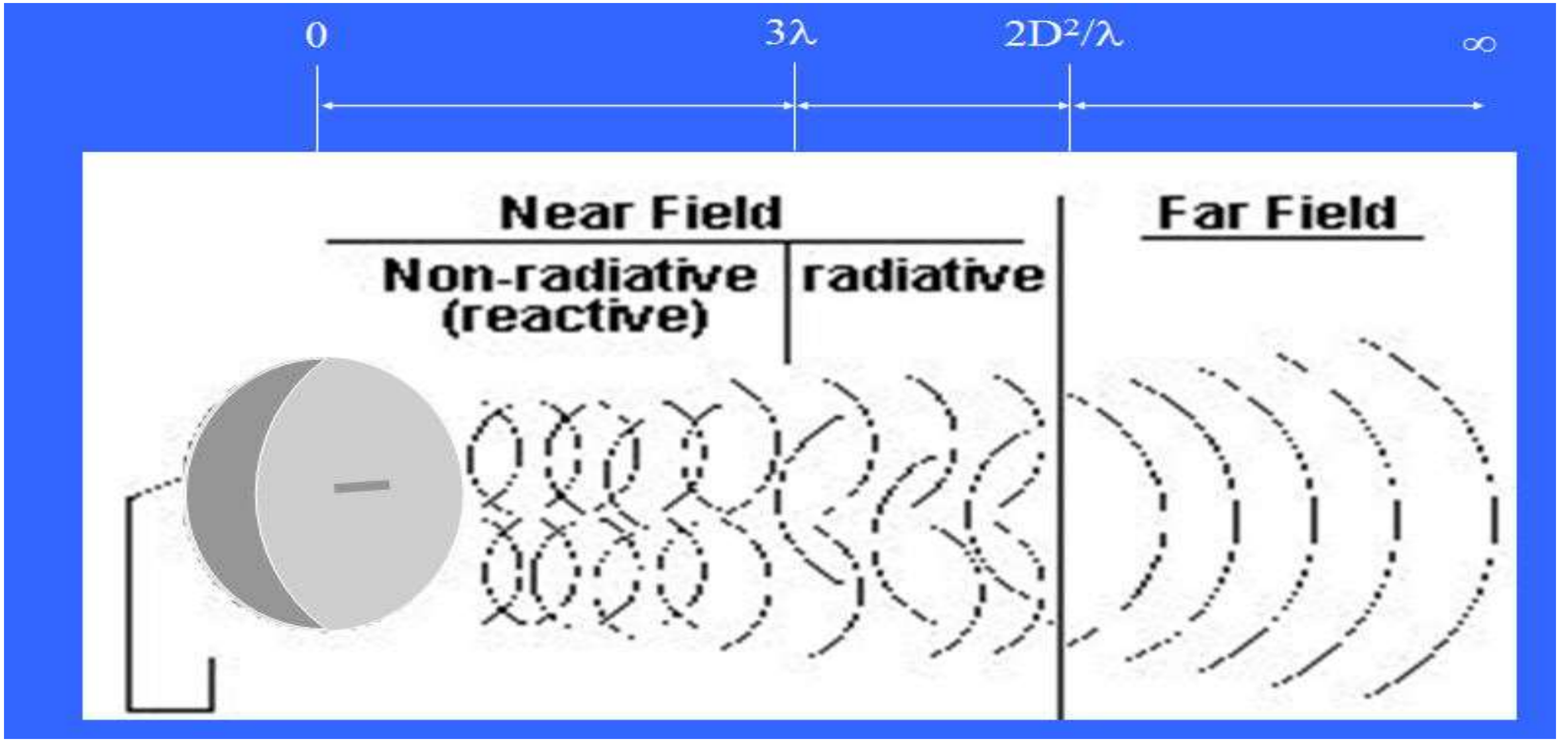


Fig: Near and Far Field regions

"Source: Antenna Measurements, http://www.ko4bb.com/Test_Equipment/Antenna_Measurements/"

Neural network

- Mathematical model inspired by biological systems.

- Artificial neural networks change the structure of the system(amplitude & phase shift) to optimize the response to training data.

Neural network goal

- The goal of neural network training is to minimize the difference between output data and the target data.
- Iterative process of adjusting coefficients until user defined threshold is reached.

Neuron definition

- Simple neuron:
  - Total Input :

    $X = \sum_{i=1}^{n} w_i I_i + b$

    (w = weights, x = n different inputs and b = bias).

  - Each neuron has its own activation function which scales and compresses the output value. ($Y = f(X)$)

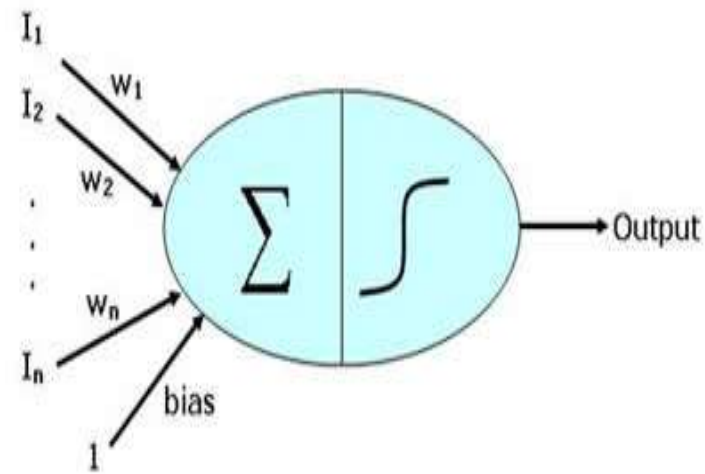


Fig: Single Neuron Design

Source: Neural Networks, http://www.emilstefanov.net/Projects/NeuralNetworks.aspx

Activation

Activation Functions

Name	Formula
Linear	$Y = X$
Sigmoid	$Y = \frac{1}{1+e^{-x}}$
Tanh	$Y = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$
Step	$Y = \begin{cases} -1 \; if \; x < 0 \\ 1 \; if \; x \geq 0 \end{cases}$

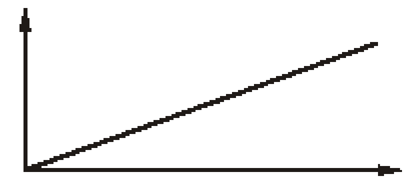


Fig: Linear

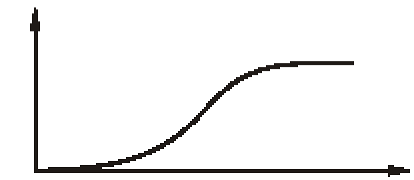


Fig: Sigmoid

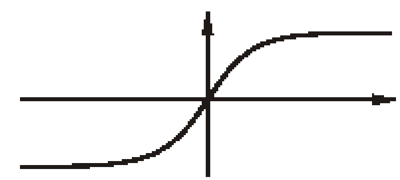


Fig: Hyperbolic Tangent

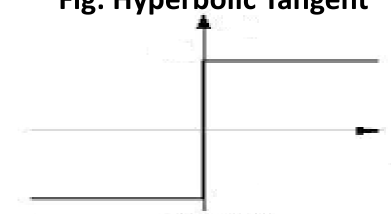


Fig: Step

Multi layer network

- More than one neurons.
- Neurons in each layer connected to the multiple neurons in next layer.

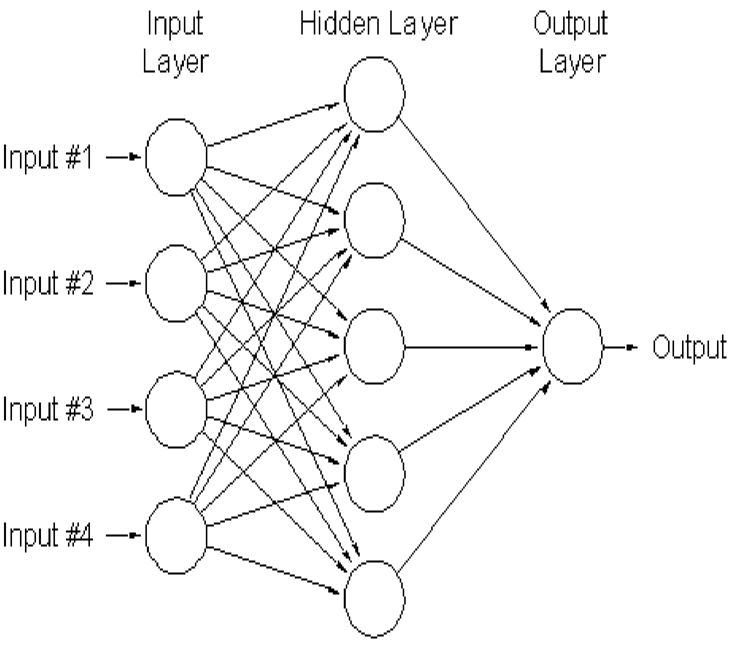


Fig: Multi Layer Neural Network

Source: BGU Computational Vision Course homepage, http://www.cs.bgu.ac.il/~icbv061/StudentProjects/ICBV061/ICBV-2006-1-TorIvry-ShaharMichal/index.php

Training Step (1)

1. User assigns predetermined training data, say Z.

2. User then feeds in input data, X.

3. The weights(w) are initialized to randomly generated value $-1 \leq w \leq 1$

4. Error from each neuron output also known as "*blame*" is calculated: $e_j = \left|Y_j - Z\right|$ (j = each iteration)

Training Step (2)

4. Neuron adjusts weights from each output using *gradient descent* method given by:
   - $w_j = w_{j-1} + r * e_j * Y_j * f'(X)$

5. Neuron also adjusts the bias value:
   - $b_j = b_{j-1} + r * e_j$, (r = learning rate)

6. Test data is fed into the neural net to estimate output.

Simulation Procedure (1)

1. Create a series of single source with definite amplitude and direction of arrival (DOA).

2. Superimpose the signal with noise and interference using randomly generated signals.

3. Use the DOA and amplitude data from step 1 to train the neural network.

Simulation Procedure (2)

4. Create a test (DOA and amplitude).

5. Apply the trained neural net to estimate the DOA and amplitude of the test signals.

6. Repeat the procedure for various positions, multiple sources, near and far field signals, multiple frequencies and multiple amplitudes.

7. Experiment with various Neural Network algorithms.

Source Location (1)

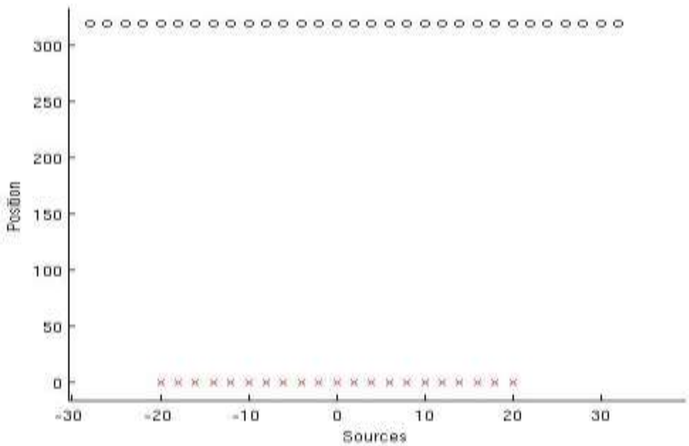


Fig: Directly Above the sensors in horizontal orientation.

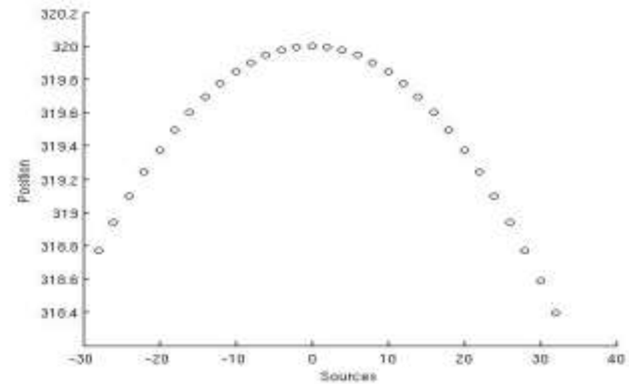


Fig: Directly Above the sensors semi-circular orientation.

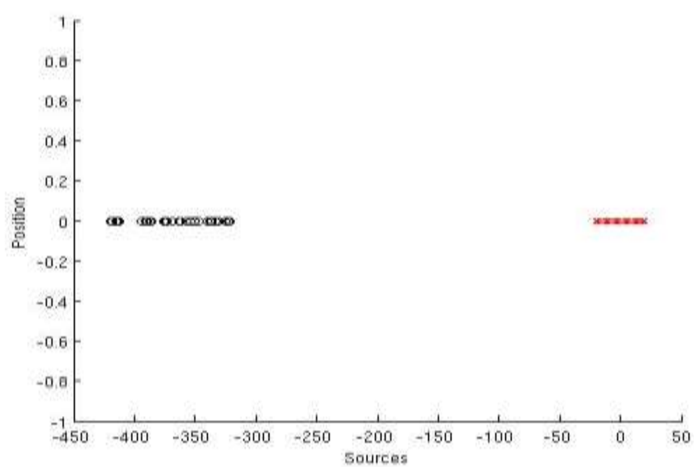


Fig: On the same horizontal axis as sensors (towards left).

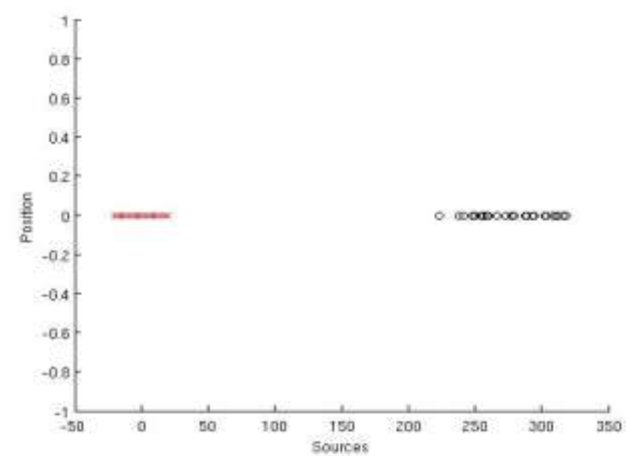


Fig: On the same horizontal axis as sensors (towards right).

Source Location (2)

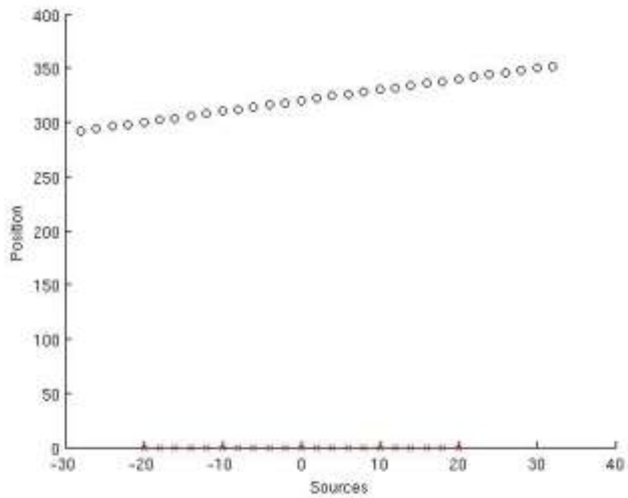


Fig: Directly Above the sensors (sloped upwards).

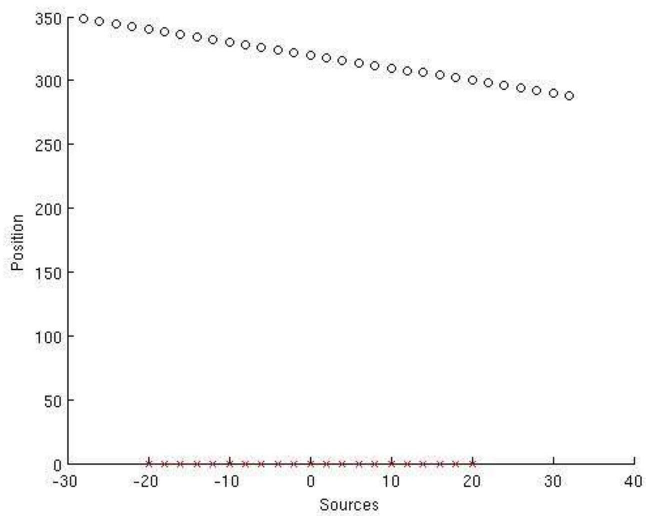


Fig: Directly Above the sensors (sloped downwards).

Single Source example

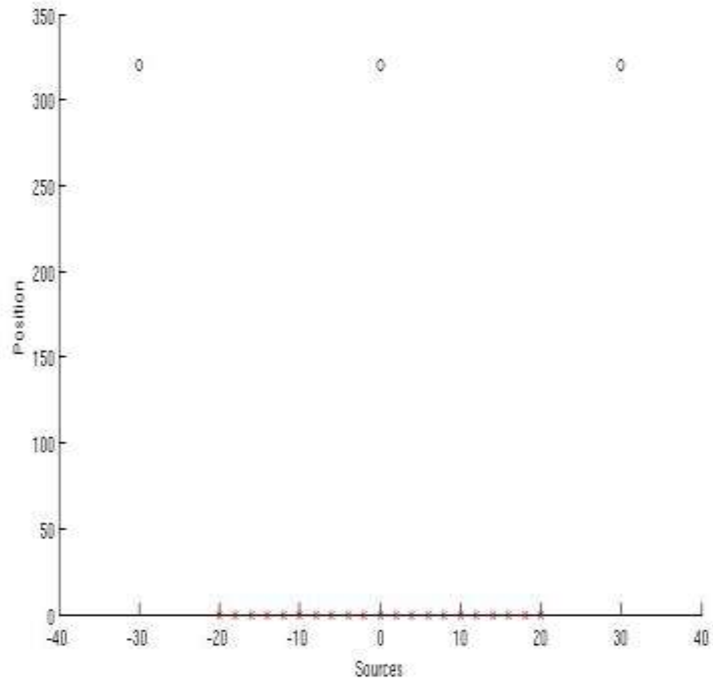


Fig: Location of Sources.

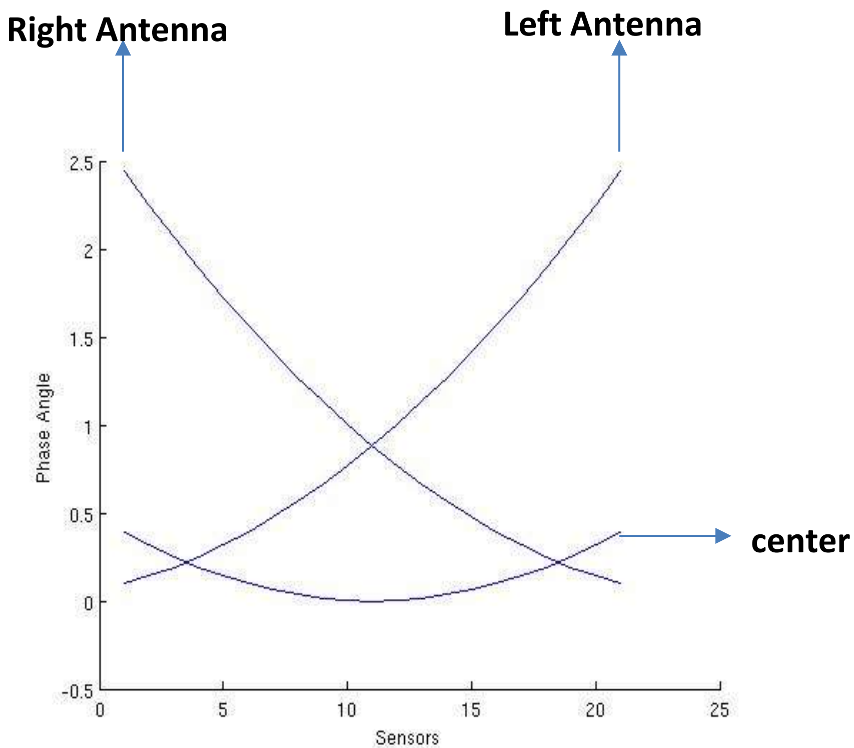


Fig: Corresponding phase shift in each sensors.

Near Field vs. Far Field (S.S.)

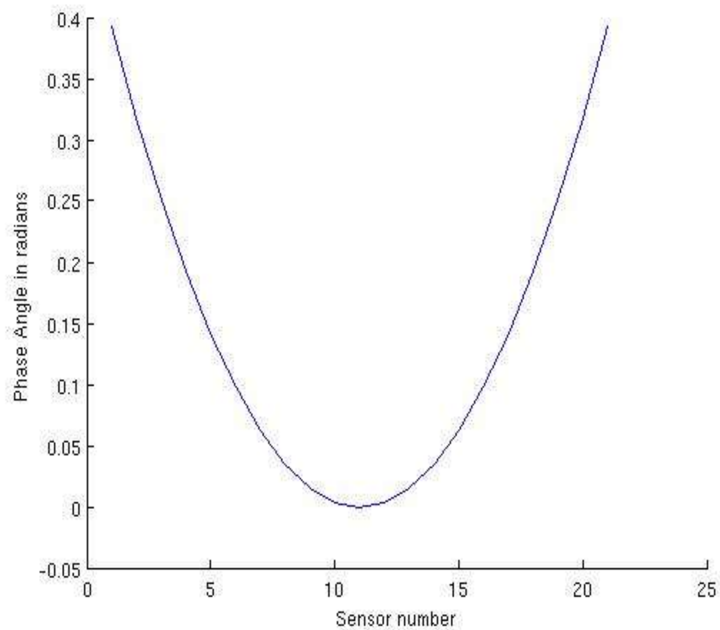


Fig: Phase shift from near field signal.

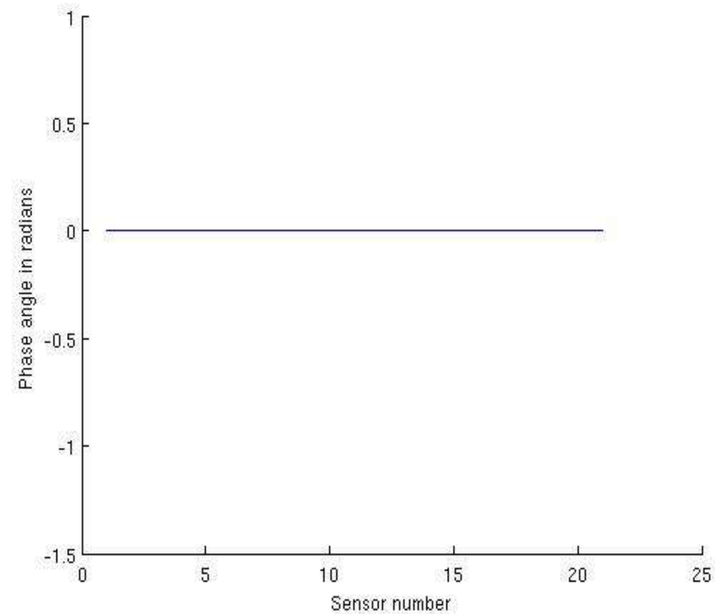


Fig: Phase shift from far field signal.

Near Field vs. Far Field (M.S.)

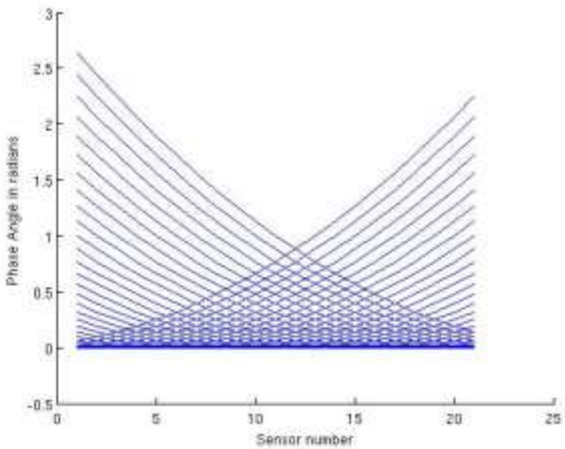


Fig: Phase shift (directly above, horizontal)

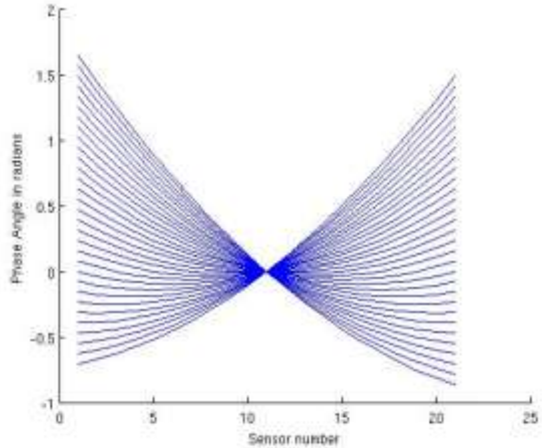


Fig: Phase shift (directly above arc)

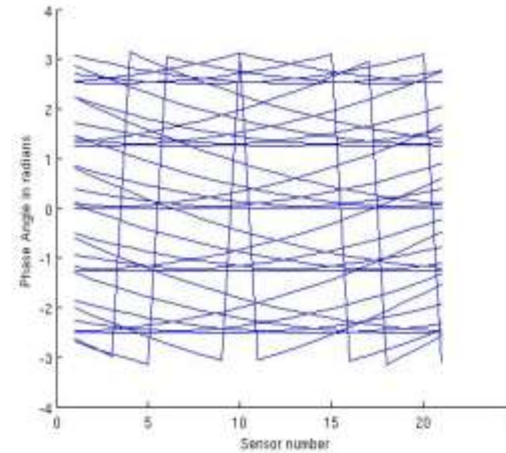


Fig: Phase shift (directly above, sloped)

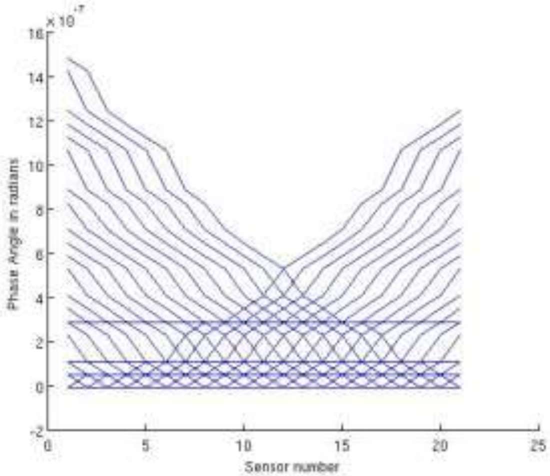


Fig: Phase shift (directly above, horizontal)

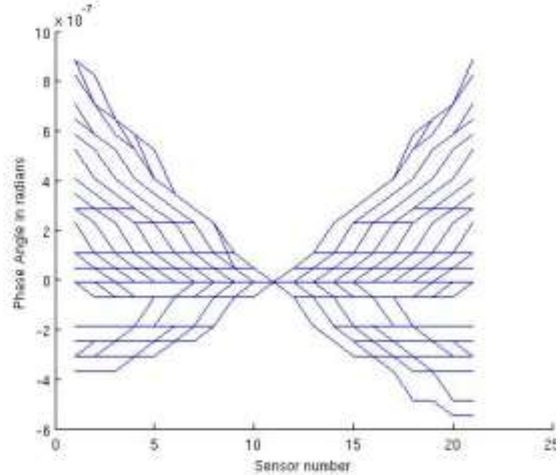


Fig: Phase shift (directly above arc)

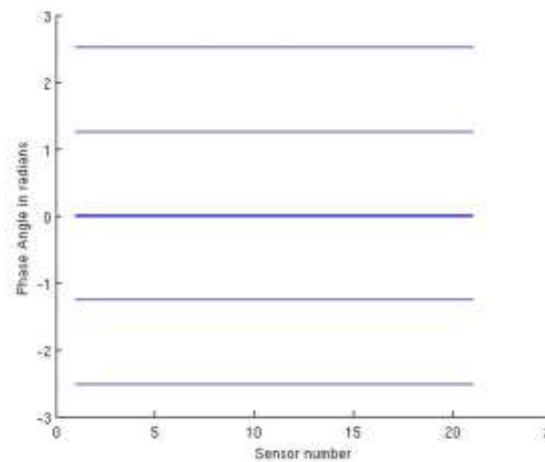
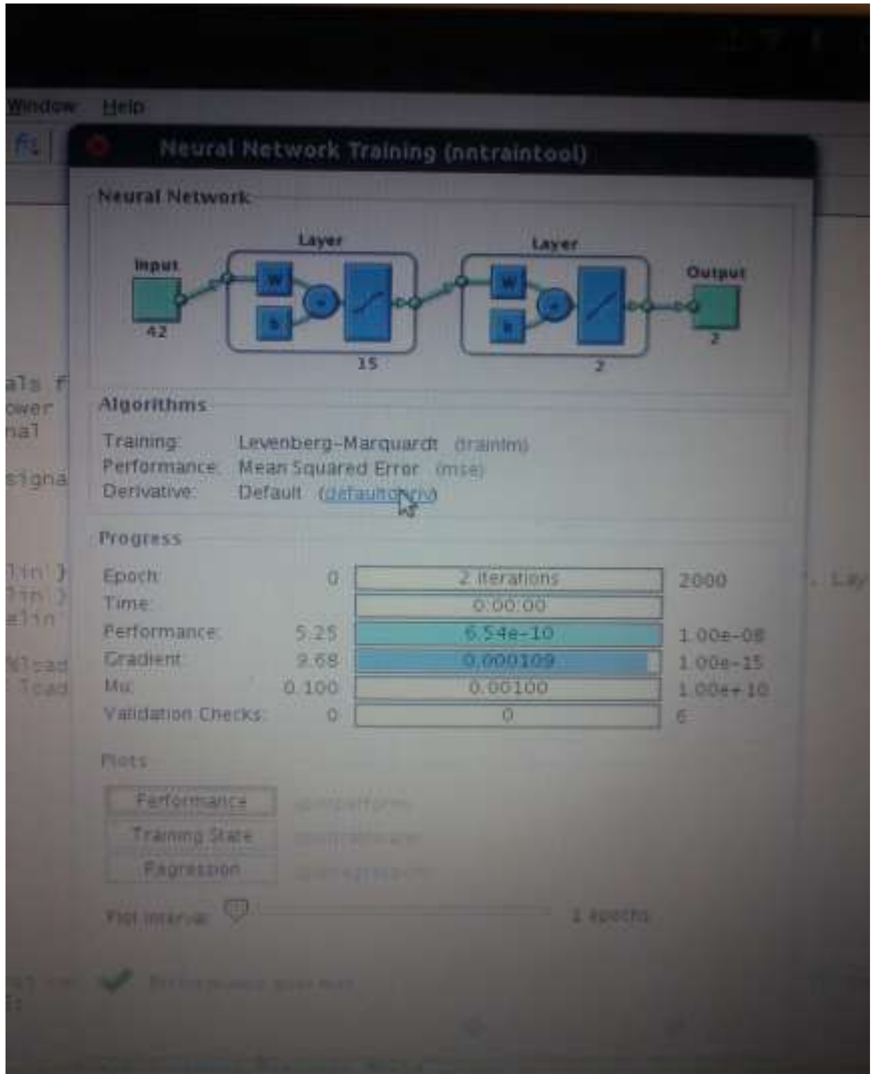


Fig: Phase shift (directly above, sloped)

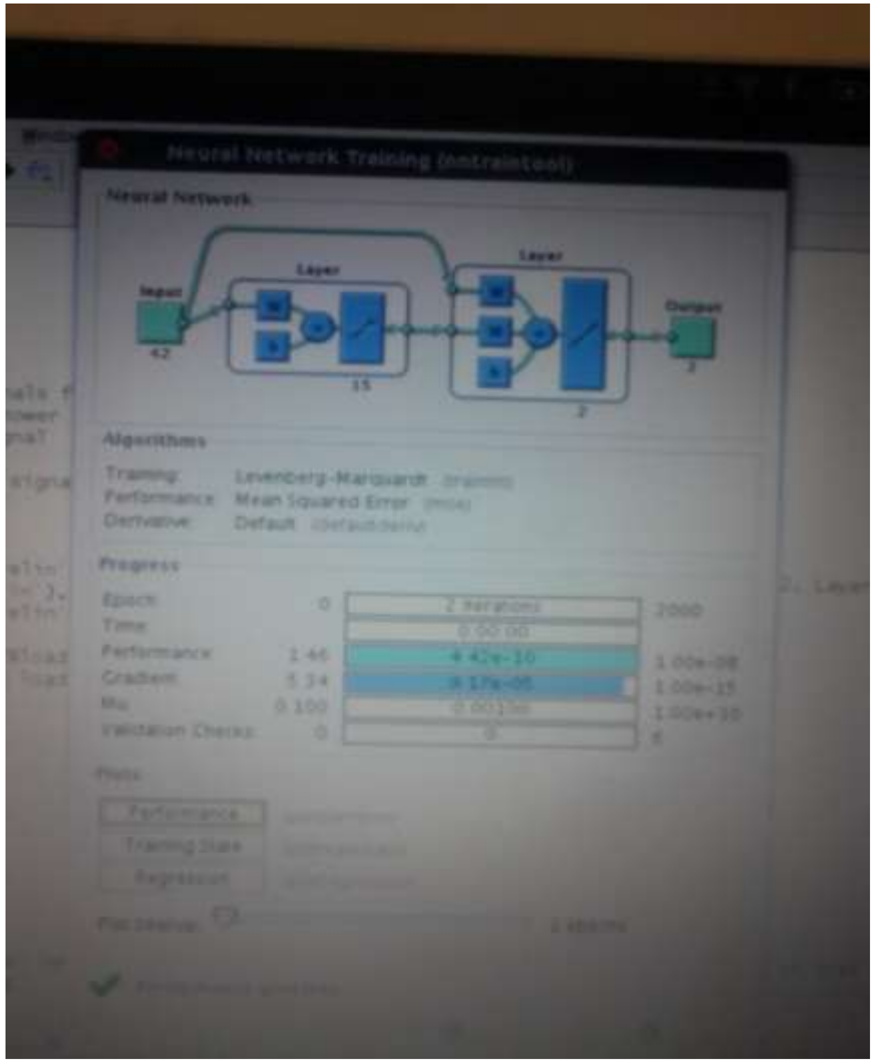
Neural Net Algorithms

- Feed Forward Back Propagation (FF/BP)
- Cascade Forward Neural Network (CF)
- Elman Neural Network (Elman)

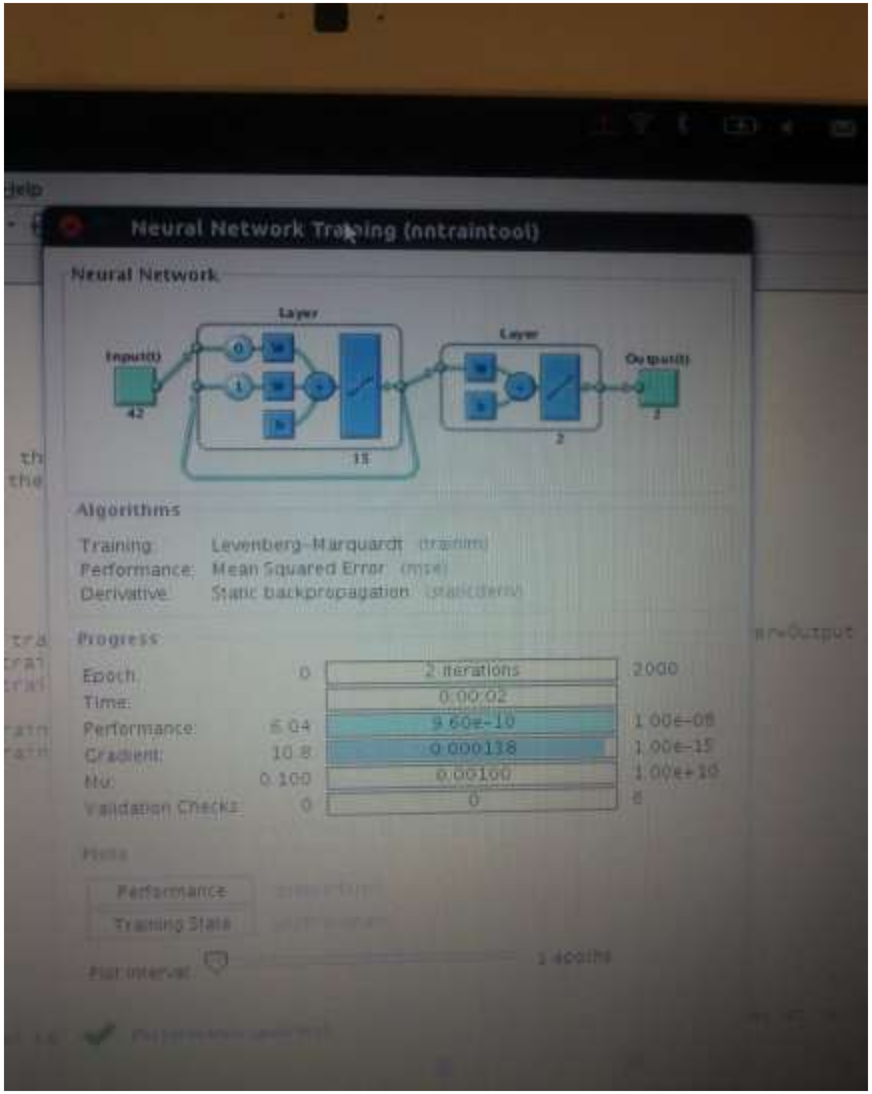
Feed Forward Back Propagation (FF/BP)



Cascade Forward (CF)



Elman


Neural Network Training (nntraintool)
Neural Network
Layer
Input(t)
42
Layer
Output(t)
15
2
2
Algorithms
Training: Levenberg-Marquardt
Performance: Mean Squared Error
Derivative: Static backpropagation
Progress
Epoch: 0 2 iterations 2000
Time: 0:00:02
Performance: 6.04 9.60e-10 1.00e-08
Gradient: 10.8 0.000138 1.00e-15
Mu: 0.100 0.00100 1.00e+10
Validation Checks: 0 0
Performance
Training State

Analysis of Results (1)

- **Estimation error in Direction of Arrival (DOA) using FF/BP**

Signal Type	Location	Estimation Error (%)
Near Field	Directly Above , Single Source	0.37
	Above (Right), Single Source	11.5
	Above (Arc), Multiple Source	3.9
	Above (Horizontal), Multiple Source	1.4
	Above (Horizontal), Different Frequencies	4.4
	Above (Horizontal), Different Amplitudes	3.5
Far Field	Directly Above, Single Source	0
	Above (Right), Single Source	0
	Above (Arc), Multiple Source	0.0008
	Above (Horizontal), Multiple Source	0.0002
	Above (Horizontal), Different Frequencies	0
	Above (Horizontal), Different Amplitudes	0

Analysis of Results (2)

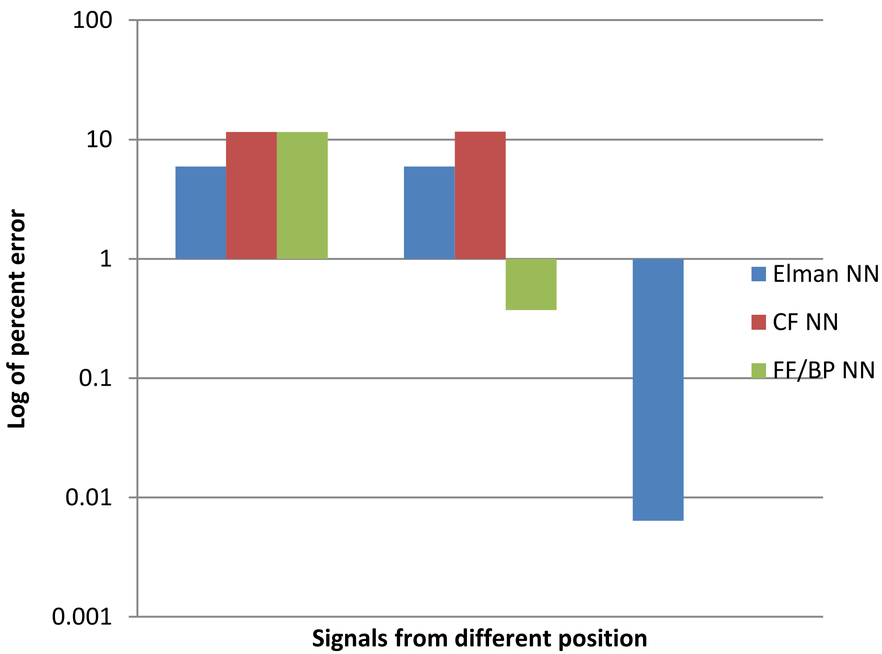
- **Estimation error in Amplitude using FF/BP**

Signal Type	Location	Estimation Error (%)
Near Field	Above (Horizontal), Different Amplitudes	5.9
Far Field	Above (Horizontal), Different Amplitudes	13.8

Single Source

- Near Field Case:

S.S. Near Field Test error for DOA

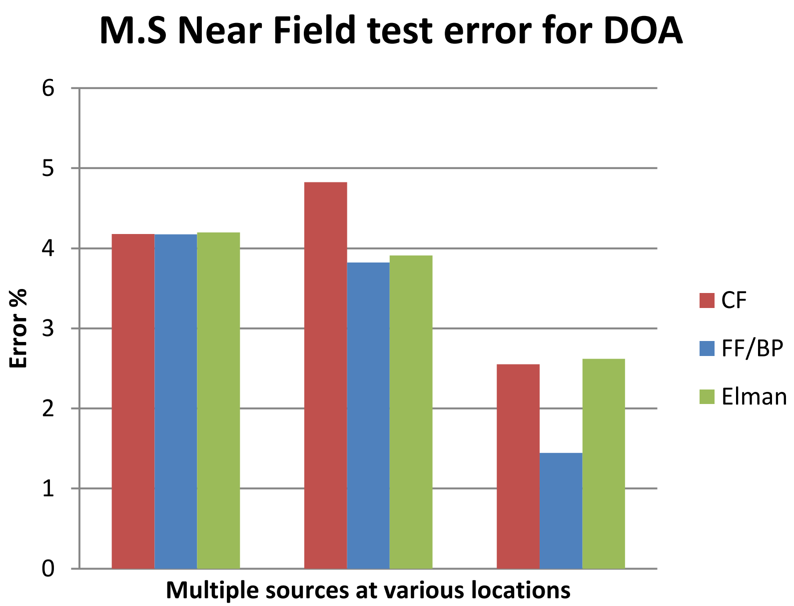


NNet / Position	Elman	CF	FF/BP
Above (Left)	5.9%	11%	11%
Above (Right)	5.9%	11%	0.37%
Directly Above	0.0064%	0%	0%

- There was very unnoticeable error for Far Field case.

Multiple Sources

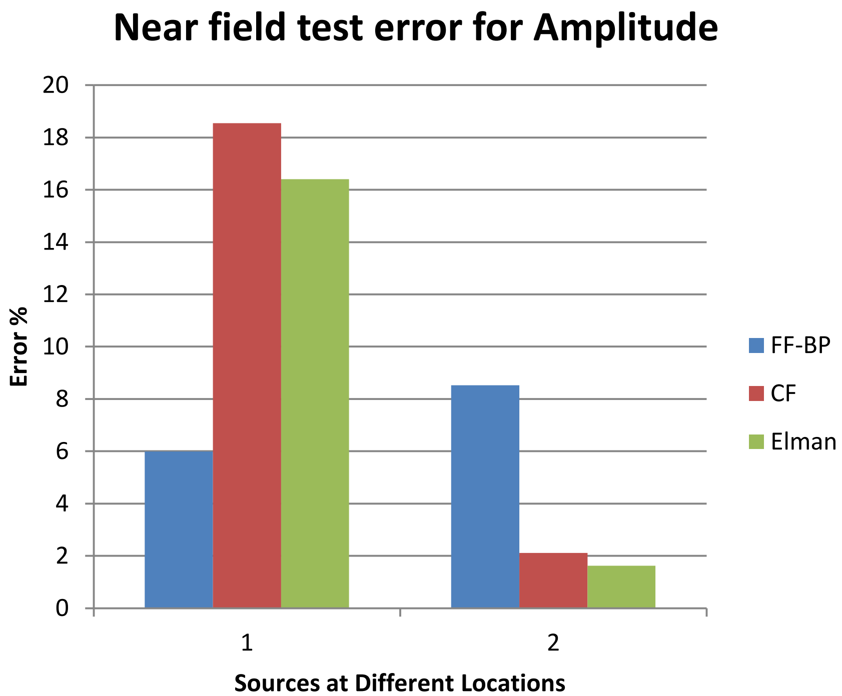
- Near Field Case:

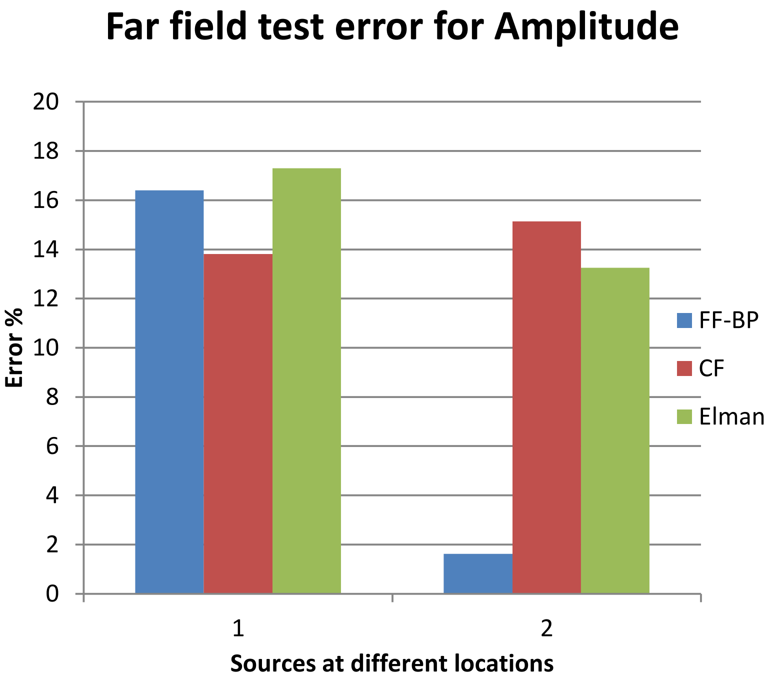


Nnet / Position	Elman	CF	FF/BP
Sloped	4.19%	4.17%	4.17%
Arc (above)	3.90%	4.82%	3.82%
Horizontal (above)	2.62%	2.55%	1.45%

- There was very unnoticeable error in Far Field case.

Different Amplitude





Conclusion

- Spherical signals from far field behave as plane waves.
- No significant difference in estimation from 3 different neural net algorithm.
- More training data gives better estimation compared to single training data.
- More training data takes more time to train the network.
- Far field takes less time training compared to near field.
- Far field for DOA has lower or no error in estimation compared to near field.
- However, Far field for amplitude has comparatively larger error than near field.

Thank you

- Dr. Dan Fleisch (Department of Physics, Wittenberg University)

- Dr. Wolfram Pannert (Department of Mechanical Engineering, University of Applied Science, Aalen)

- Dr. Maria-Teresa Herd (Department of Physics, Earlham College)

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- Orr. Introduction to Radial Basis Function Networks.

Questions?