Beamforming with Neural Network

Manas Mudbari

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 electromagnetic 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

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

Working principle (1)

- General Equation for spherical signal:

\[ \vec{X} = \frac{A}{|\vec{r}|} e^{-i(\vec{k} \cdot \vec{r} - \omega t)} , \quad (\vec{r} = x \hat{x} + y \hat{y} + z \hat{z}) \text{ and } |\vec{k}| = \frac{2\pi}{\lambda} \]
Working Principle (2)

- Each array element only receives signal with value

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

- 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

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:
    \[ X = \sum_{i=1}^{n} w_i I_i + b \]
    
    (\(w = \text{weights}, \ x = n \text{ different inputs and } b = \text{bias}\)).
    
    – Each neuron has its own activation function which scales and compresses the output value. \((Y = f(X))\)

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

### Activation Functions

<table>
<thead>
<tr>
<th>Name</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>$Y = X$</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>$Y = \frac{1}{1+e^{-x}}$</td>
</tr>
<tr>
<td>Tanh</td>
<td>$Y = \frac{e^x - e^{-x}}{e^x + e^{-x}}$</td>
</tr>
<tr>
<td>Step</td>
<td>$Y = \begin{cases} -1 &amp; \text{if } x &lt; 0 \ 1 &amp; \text{if } x \geq 0 \end{cases}$</td>
</tr>
</tbody>
</table>

![Fig: Linear](image)
![Fig: Sigmoid](image)
![Fig: Hyperbolic Tangent](image)
![Fig: Step](image)
Multi layer network

• More than one neurons.

• Neurons in each layer connected to the multiple neurons in next layer.

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:
   \[ w_j = w_{j-1} + r \cdot e_j \cdot Y_j \cdot f'(X) \]

5. Neuron also adjusts the bias value:
   \[ b_j = b_{j-1} + r \cdot e_j, \quad (r = \text{learning rate}) \]

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
Analysis of Results (1)

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

<table>
<thead>
<tr>
<th>Signal Type</th>
<th>Location</th>
<th>Estimation Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Near Field</strong></td>
<td>Directly Above, Single Source</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>Above (Right), Single Source</td>
<td>11.5</td>
</tr>
<tr>
<td></td>
<td>Above (Arc), Multiple Source</td>
<td>3.9</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Multiple Source</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Different Frequencies</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Different Amplitudes</td>
<td>3.5</td>
</tr>
<tr>
<td><strong>Far Field</strong></td>
<td>Directly Above, Single Source</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Above (Right), Single Source</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Above (Arc), Multiple Source</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Multiple Source</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Different Frequencies</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Above (Horizontal), Different Amplitudes</td>
<td>0</td>
</tr>
</tbody>
</table>
Analysis of Results (2)

- Estimation error in Amplitude using FF/BP

<table>
<thead>
<tr>
<th>Signal Type</th>
<th>Location</th>
<th>Estimation Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Near Field</td>
<td>Above (Horizontal), Different Amplitudes</td>
<td>5.9</td>
</tr>
<tr>
<td>Far Field</td>
<td>Above (Horizontal), Different Amplitudes</td>
<td>13.8</td>
</tr>
</tbody>
</table>
Single Source

- Near Field Case:

**S.S. Near Field Test error for DOA**

<table>
<thead>
<tr>
<th>NNet</th>
<th>Elman</th>
<th>CF</th>
<th>FF/BP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Above (Left)</td>
<td>5.9%</td>
<td>11%</td>
<td>11%</td>
</tr>
<tr>
<td>Above (Right)</td>
<td>5.9%</td>
<td>11%</td>
<td>0.37%</td>
</tr>
<tr>
<td>Directly Above</td>
<td>0.0064%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

- There was very unnoticeable error for Far Field case.
Multiple Sources

• Near Field Case:

<table>
<thead>
<tr>
<th>Position</th>
<th>Nnet</th>
<th>Elman</th>
<th>CF</th>
<th>FF/BP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sloped</td>
<td>4.19%</td>
<td>4.17%</td>
<td>4.17%</td>
<td></td>
</tr>
<tr>
<td>Arc (above)</td>
<td>3.90%</td>
<td>4.82%</td>
<td>3.82%</td>
<td></td>
</tr>
<tr>
<td>Horizontal (above)</td>
<td>2.62%</td>
<td>2.55%</td>
<td>1.45%</td>
<td></td>
</tr>
</tbody>
</table>

There was very unnoticeable error in Far Field case.
Different Amplitude

Near field test error for Amplitude

Far field test error for 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)
Bibliography

• McClellan, Schafer, Yoder. DSP First, A Multimedia Approach

• Gurney. An Introduction to Neural Networks

• Dayhoff, Neural Network Architectures.

• http://www.engr.wisc.edu/ece/faculty/vanveen_barry/ASSP_Mag_88.pdf

• http://www.htw-aalen.de/personal/img/publikationen/1028_JAA-Spatial_smoothing_for_localized_correlated_sources.pdf

• www.antenna-theory.com

• Tucker. Introduction to Phased Array Design.

• Orr. Introduction to Radial Basis Function Networks.
Questions?