EECS 463
Adaptive Filters Project

Adaptive Filters for Acoustic Noise Suppression
Project Goals

1. Identify the Problem of Acoustic Noise in Speech Communications
2. Discuss Techniques for Suppressing Acoustic Noise
   1. Spectral Attenuation
   2. Microphone Arrays
   3. Blind Source Separation
3. Discuss Current Limitations and Possible Future Direction

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The Acoustic Noise Problem

1. Classic Problem in the Field of Audio and Speech Processing
   1. Noise is Everywhere!
   2. Most Speech Telecommunications lack Visual Cues and Directional Hearing

- Why Adaptive Filters?
  - Spectral Overlap of Noise and Speech or Audio
  - Continuously Changing Acoustic Environment

1. Applications
   1. Hearing Aid Design
   2. Teleconferencing
   3. Speech Recognition
   4. **Mobile Communications**

   People can be anywhere and expect to communicate!

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The Noisy Environment

- Background "Noise"
- Interfering Talkers
- Reverberation
- Echo
## Noise Classification

<table>
<thead>
<tr>
<th></th>
<th>Examples</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Diffuse&quot; Noise</td>
<td><em>car wind noise</em></td>
<td>stationary</td>
</tr>
<tr>
<td>(noise with little</td>
<td><em>restaurant babble noise</em></td>
<td><em>sometimes stationa**y</em></td>
</tr>
<tr>
<td>directionality)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;Coherent&quot; Noise</td>
<td><em>overhead projector fan</em></td>
<td>stationary</td>
</tr>
<tr>
<td>(noise from a specific direction)</td>
<td><em>stereo system</em></td>
<td>non-stationary</td>
</tr>
<tr>
<td></td>
<td><em>interfering talkers</em></td>
<td>non-stationary</td>
</tr>
<tr>
<td>&quot;Convolutive&quot; Noise</td>
<td><em>acoustic echo</em></td>
<td>non-stationary</td>
</tr>
<tr>
<td>(convoluted version of signal through impulse response)</td>
<td><em>reverberation</em></td>
<td>non-stationary</td>
</tr>
</tbody>
</table>

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Spectral Attenuation

- Classic Solution to Noise Suppression ....... and the most popular
- Based on Well Known Adaptive Filtering Model and MMSE Optimization
- Frequency Domain Gives Better Separation of Speech and Noise and Better Fit to Human Auditory Model

\[
x(t) = s(t) + d(t)
\]

\[
Y_n(k) = S_n(k) = G_n(k) \cdot Y_n(k)
\]

**optimal gain solution**

\[
G_n(k) = \frac{E\{ |S_n(k)|^2 \}}{E\{ |S_n(k)|^2 \} + E\{ |D_n(k)|^2 \}}
\]

\[
G_n(k) = \frac{\xi_n(k)}{1 + \xi_n(k)}
\]

\[
\xi_n(k) = \frac{E\{ |S_n(k)|^2 \}}{E\{ |D_n(k)|^2 \}}
\]

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Spectral Attenuation Implementation

\[ Y_n(k) = G_n(k) \cdot |X_n(k)| \cdot \exp(j \angle X_n(k)) \]

\[ \xi_n(k) = \alpha \gamma_{n-1}(k) \cdot G_{n-1}^2(k) + (1 - \alpha)(\gamma_n - 1) \]

\[ a \text{ posteriori SNR} \]

\[ \gamma_n = \frac{|X_n(k)|^2}{\lambda_n(k)} \]

\[ a \text{ priori SNR} \]

\[ \lambda_n(k) \]

\[ \text{noise power estimate} \]

\[ G_n(k) = f(\xi_n(k), \gamma_n(k)) \]

\[ \text{gain function varies in implementation} \]

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Noise Power Estimation

• Primary Limitation of Spectral Attenuation Algorithm
  • Usually assume...........
    1. Speech and Noise Statistically Independent
    2. Speech Not Always Present
    3. Noise More Stationary than Speech

• Voice Activity Detection
  – Monitor change in energy of signal
  – Determine if Noise or Speech Frame
  – Update Noise Power Spectrum if Noise Frame

• Minimum Statistics
  – Track the Minimum Value of Noisy Speech Spectrum
  – \( \lambda_n(k) = C \cdot \min_{l=0,1,...,L_{ms}} \{ |X_{n-l}(k)|^2 \} \)
  \[ |X_n(k)|^2 = \beta \cdot |X_{n-1}(k)|^2 + (1 - \beta) \cdot |X_n(k)|^2 \]
Spectral Attenuation Performance

- Good Performance for Stationary Noise
- Very Poor Performance for Non-Stationary Noise
- More Noise Reduction Leads to Audio Artifacts (musical tones, etc.) and less Speech Intelligibility
Adaptive Microphone Arrays

- Take Advantage of Spatial Distribution of Noise by using Multiple Mics
- Target Source Signal and Suppress Indirect Signals
- Increase in Noise Reduction has Direct Impact on Speech Intelligibility
- Adaptive Array can Change Directivity Pattern When Noise Locations are not Assumed Fixed

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Adaptive Filter and Sum Beamformer

- Adapt Filter Coeffs to Minimize Output Power while Giving Fixed Target Response
- Use Gradient Descent Approach with Instantaneous Estimates to Solve (LMS with constraints)

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Adaptive Array Performance

- Works very well for Coherent Noise, Not So Well for Diffuse Noise
- Most Practical Applications have Limited Space for Multiple Mics
- Could be Useful in Providing Better Noise Estimate to Spectral Attenuation Algorithm

7 mics, d = 50cm, 1.5sec adaptation time, noise source at 45deg
Are We Getting Anywhere?

Spectral Attenuation can suppress............
   Highly Stationary Noise, Diffuse or Coherent

Adaptive Mic Arrays can suppress............
   Coherent Noises, Stationary or Non-Stationary

But what if the acoustic environment is completely unknown?

What if we can make no assumptions on the locations of noise sources or the primary talker?

What about convolutive noise such as reverb?

   Blind Source Separation
   Separate Signal from Noise “Blindly”
Blind Source Separation

\( M \) Microphones Recording \( N \) Independent Sources

\[
x_i = a_{i1}s_1 + a_{i2}s_2 + \ldots + a_{in}s_n
\]

*If sources are an instantaneous mix, the \( a_i \)'s are scalars*

*If sources are a convolutive mix, the \( a_i \)'s are FIR filters*

Need to Separate Noise Sources from Signal Source

<table>
<thead>
<tr>
<th>Source Signals</th>
<th>Mixing Matrix</th>
<th>Mixed Signals</th>
<th>Separation System</th>
<th>Separated Signals</th>
</tr>
</thead>
<tbody>
<tr>
<td>([s_1(t) \ldots s_N(t)])</td>
<td>([a_{11}(l) \ldots a_{1M}(l) \ldots a_{NM}(l)])</td>
<td>([x_1(t) \ldots x_M(l)])</td>
<td>([w_{11}(l) \ldots w_{iM}(l) \ldots w_{NM}(l)])</td>
<td>([y_1(t) \ldots y_N(t)])</td>
</tr>
</tbody>
</table>

*Obvious Solution is \( y = A^{-1}x \) where \( x = As \) But We Don’t Know \( A \) or \( s \)!

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BSS through Independent Component Analysis (ICA)

- ICA looks for components that are Independent
- Assumptions are that the Independent Sources are Non-Gaussian
- Central Limit Theorem
  - Summation of Gaussian Signals will lead to a more Gaussian Distribution
  - If we find a Transformation that is Maximally Non-Gaussian, the Transformed Signals must be the Independent Components
Methods of ICA

- **Maximum Non-Gaussianity**
  - use Kurtosis as measure of Non-Gaussianity \( \text{kurt}(y) = E\{y^4\} - 3(E\{y^2\})^2 \)
  - Can use Gradient Descent Approach with Kurtosis as the Cost Function
  - Can use Recursive Algorithms like FastICA

- **Maximum Likelihood Estimation**
  - Find Parameters that give Highest Probability from Observations
  - Close relationship to Neural Network Theory, Maximizing Output Entropy
  - InfoMax Algorithm
    - also has a Gradient and FastICA Algorithm

- **Non-Linear Decorrelation (Higher Order Statistics)**
  - Decorrelation Doesn’t Prove Independence, but Decorrelation of a Non-Linear Function Does
    - Jutten, Herault, and Ans (late 1980’s)
    - \( y_1 = x_1 m_{12} - y_2 \)
    - \( y_2 = x_2 m_{21} - y_1 \)
    - \( \Delta m_{12} = \mu \cdot f(y_1)g(y_2) \)
    - \( \Delta m_{21} = \mu \cdot f(y_2)g(y_1) \)
    - \( f(\cdot), g(\cdot) \) are odd non-linear functions
    - adapt coefficients until
    - \( E\{f(y_1)g(y_2)\} = E\{f(y_2)g(y_1)\} = 0 \)
Practical Considerations of ICA

• Permutation and Scaling Ambiguity
• Frequency Domain or Time Domain?
  – Frequency Domain
    • makes solving for Convolution Mixes Easier
    • Permutation and Scaling Ambiguity Occurs in Every Frequency Bin
    • Solutions for Permutation problem based on Assumptions of Deterministic Change in Energy across Audio Frames
  – Time Domain
    • Solving for Convolution Mix Require Heavy Computation and can Result in Large Filters
  – Some Proposed Methods use both Time and Frequency Domain
• What if Number of Sources > Number of Sensors?
• Diffuse Noise leads to Non-Optimal Results
• Not a Good Solution for Diffuse Noise Suppression
BSS Performance

- Very Mixed Results in Real Acoustic Environments (reverberation)
- Upper Bounded by Adaptive Beamformer Performance, but is much more adaptable than the Beamformer
Conclusions

• BSS Techniques are Currently Evolving
• Spectral Attenuation and Adaptive Arrays well Proven, but Limited
• Future Noise Suppression Algorithms may likely be a Combination of all Methods!