Speaker Recognition
An Outline of Neural Network-Based Approaches

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Overview

What is Speaker Recognition?

Preliminary Principles

A detailed look at the process.

Neural Network Methods

Two Different Approaches
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In General

- **Input**: Audio encoding of speech
- **Output**: Information that classifies speaker

Applications:
- User authentication
- Biometrics
- Caller ID
- ...
Paradigms

- **Speaker Recognition**
  Recognize that a member of a known population spoke

- **Speaker Verification**
  Verify that a given subject is who he claims to be

- **Speaker Identification**
  Detect a particular speaker from a known population
  - Text Dependent
  - Text Independent
Approaches

- **Acoustic Phonetic**
  Based on theory that speech can be broken down uniquely into phonemes that can then be easily characterized and used to categorize future inputs

- **Pattern Recognition**
  The ‘brute force’ approach: if enough samples are trained, common features will be accentuated and recognized

- **Artificial Intelligence**
  Combination of the above; systematic approach to emulate human recognition and extraction of signal features for pattern matching
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Speech Signal

Preprocessing

Feature Extraction

Training

Reference

Pattern Matching

Unknown

Recognition Engine

Decision Rule

Identification Result
Preprocessing

- Digital filtering
  - Noise Removal
  - Level Adjustment
  - Frequency Attenuation
- Endpoint detection
Feature Extraction

We need to obtain characteristic values of the sound sample. Why? How?

- Discrete Fourier Transform
- Power Spectral Density
- Linear Predictive Coding
- Average Mean Distance function

All three methods give us *numbers*, which Neural Networks like for input. These numbers should be unique and characteristic of the sound samples they were generated from.
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What are they?

- **Discrete Fourier Transform**
  Algorithm to move from continuous signal to discrete frequency domain

- **Power Spectral Density**
  Computed from the DFT, unique spectral representation of a signal

- **Linear Predictive Coding**
  Used to represent the logarithmic power spectrum of a signal in compressed form

- **Average Mean Distance function**
  Used to find the fundamental frequency of a signal
Example of DFT spectra
Example of PSD graphs
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Neural Network Methods
Two Different Approaches
Multi-Layer Perceptrons

Basic three-layer feed-forward network

Input layer  Hidden layer  Output layer
Multi-Layer Perceptrons

Basic three-layer feed-forward network

Positives:

- Simple to train
- Simple to understand
- Good accuracy on trained samples; up to 100%

Negatives:

- Possibility of overfitting data
- Bad results on untrained or new data
- Better suited to text-dependent recognition
Self Organizing Maps

- Much more robust than MLP
- Use the SOM as a map of codewords
Self Organizing Maps

• Much more robust than MLP
• Use the SOM as a map of codewords
Figure 1: The topological property of the SOM: neighboring units on the SOM are associated with neighboring codewords.
Self Organizing Maps

- Much more robust than MLP
- Use the SOM as a map of codewords
- Similar words will be neighbors in the map
  - Sample input can then be made into an occupancy histogram
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## SOM Experiment Results

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>clean</th>
<th>30 dB</th>
<th>20 dB</th>
<th>10 dB</th>
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<tr>
<td>LPC/SOM</td>
<td>98,2</td>
<td>95,0</td>
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<td>95,5</td>
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<tr>
<td>MFCC/AHSM</td>
<td>98,6</td>
<td>96,4</td>
<td>68,9</td>
<td>27,6</td>
</tr>
</tbody>
</table>

- 100 speakers, 100 speech samples per speaker
- 25x25 Self-Organizing Map
Summary

- Speaker/Voice recognition can be accurately done by clever usage of a neural network
- Multi-Layer Perceptrons and Self Organizing Maps are two network types that have been adapted for this purpose