# A Simple Overview of Monaural Speech Enhancement

——focusing on the case of additive independent noise

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# 景

- 问题描述
- 方法分类
- 典型算法

# 问题描述

- 背景
  - 语音混杂着噪声——如何获取干净的语音?
- 目的
  - perceived quality 感知质量
  - intelligibility 清晰度和可理解性
- Our focus
  - denoise

# 数学模型

- 前提
  - the noise is additive and independent of the clean speech
- 模型
  - 带噪语音信号序列是原始语音信号序列和噪音信号序列之和

$$s(k) = f(s(k-1), \dots, s(k-K), \mathbf{w}) + v(k)$$
$$y(k) = s(k) + n(k)$$

# 语音的特性

- 非线性&非平稳性
  - 音素内和音素之间的快速片段过渡
  - 清音期间的湍流激励
  - 浊音期间的声门打开/闭合
- 线性&平稳性
  - 短时线性时不变
  - 短时平稳信号

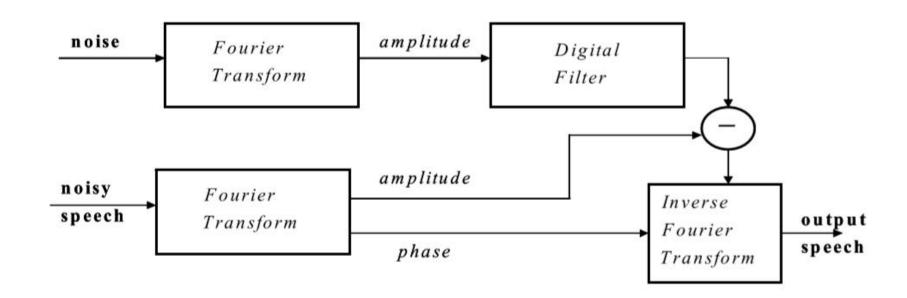
# 方法分类

- Spectral Subtraction/Filtering Techniques
  - Spectral Subtraction (SS)
  - Wiener filtering
  - Kalman Filtering
  - Signal Subspace approach
- Neural Network Based Techniques

# Spectral Subtraction (SS)

• 前提: Speech and noise are assumed to be uncorrelated

• 思想: 整体的短时能量谱减去噪声的短时能量谱



# Spectral Subtraction (SS)

- 优势
  - 简单、有效、直观
- 缺陷

- $\left|\hat{S}(\omega)\right|^{2} = \begin{cases} \left|Y(\omega)\right|^{2} \left|\hat{N}(\omega)\right|^{2} & \text{if } \left|Y(\omega)\right|^{2} > \left|\hat{N}(\omega)\right|^{2} \\ 0 & \text{otherwise} \end{cases}$
- $\hat{s}(k) = IFFT \left[ \left| \hat{S}(\omega) \right| e^{j \arg(Y(\omega))} \right]$
- 没有估计原始相位信息,而使用混合信号的相位信息做逆变换,造成失真
- 对相减结果出现的负值直接置零,转换回时域后引入"音乐噪声"
- 拓展方向
  - Spectral Subtraction With Oversubtraction Model
  - Non-Linear Spectral Subtraction

# Spectral Subtraction (SS)

Spectral Subtraction With Oversubtraction Model

• 
$$\alpha$$
:过減因子
•  $\beta$ :谱下限
$$|\hat{S}(\omega)|^2 = \begin{cases} |Y(\omega)|^2 - \alpha |\hat{N}(\omega)|^2 \text{ if } |Y(\omega)|^2 - |\hat{N}(\omega)|^2 > \beta |\hat{N}(\omega)|^2 \\ \beta |\hat{N}(\omega)|^2 \text{ otherwise} \end{cases}$$

- Non-Linear Spectral Subtraction
  - Φ is a non-liner function

$$\left| \hat{N}(\omega) \right|_{nl}^{2} = \Phi\left( \max_{over M \ frames} \left( \left| \hat{N}(\omega) \right|^{2} \right), R_{post}(\omega), \left| \hat{N}(\omega) \right|^{2} \right)$$

$$R_{post}(\omega) = \left( \left| Y(\omega)^{2} \right| / \left| N(\omega)^{2} \right| \right) - 1$$

# Wiener filtering

$$\frac{x = s + v}{\longrightarrow} h \longrightarrow y = \hat{s}$$

#### • 前提:

• 语音和噪声均为广义平稳过程且知它们的二阶统计特性

#### • 思想:

- 利用信号和噪音的自相关函数来获得最小均方误差(MMSE)意义下对线性滤波器最优预测
  - 本质上是一个线性最小均方差估计器(LMMSE estimator)

#### • 限制

- 维纳滤波器是在一维平稳状态下的线性最优估计器,只有输入信号是统计意义上是平稳信号时,其增益函数解才是最优解
- 仅仅考虑了量测方程,并没有关心信号本身的变化规律

# Kalman filtering

#### • 前提

- 动力学模型是线性的,量测模型也是线性的
- 状态噪声和量测噪声均为零均值的白噪声
- 两种噪声,以及噪声与状态之间互不相关

#### • 思想

• 粗略地讲,Kalman filter就是一种可以recursively执行的,结合了线性系统动态方程的Wiener filter。

# Extended Kalman filtering

$$s(k) = f(s(k-1), \dots, s(k-K), \mathbf{w}) + v(k)$$
$$y(k) = s(k) + n(k)$$

- 模型
  - 语音时域模型为非线性自回归模型
    - v(k) 是状态方程中的过程噪音,通常认为是白噪声
- 思想
  - 用一个时变线性函数作为非线性函数f(·)的近似

# Signal Subspace approach

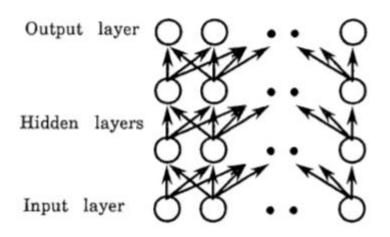
- 前提
  - Assuming the signal and noise are stationary
- 思想
  - Decompose the vector space of the noisy signal into a signal-plusnoise subspace and a noise subspace.
  - Enhancement is performed by removing the noise subspace and estimating the clean signal from the remaining signal subspace.
- 缺陷:
  - 子空间正交的假设在实际情况下并不精确
  - 对非平稳噪声的效果较差

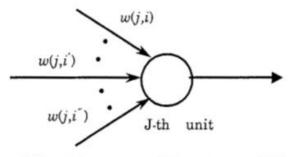
### Neural Network Based Approaches

- Neural Networks as nonlinear filters mapping the noisy speech to clean speech in the time domain or in different domains
- A time variant model can be achieved by creating different fixed models for corresponding dynamical regimes of the signals and switching between these models during the speech enhancement process.

### The Tamura approach

- 前提
  - availability of a clean speech training set
  - additive noise (non-stationary)
- 结构
  - the input and output of the network is given by the waveform itself,
     the units on the output and input layers are all linear units
  - Learning by Error Back-Propagation
- 缺陷
  - Attenuates many high frequency components in the actual speech

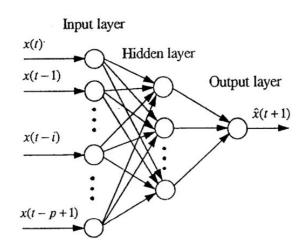




J-th unit's output =  $f(\sum w(j,i)o(i) + \theta(j))$ ,

where f(x) = 1/(1 + exp(-x)) is the sigmoid function,  $\theta(j)$ , the bias value of j-th unit and w(j,i), the link weight from the i-th unit to the j-th unit

# Speech Signal Restoration Using an Optimal Neural Network Structure



#### 目标

 Select the optimal coniplexity of the network structure so that the network can remove the noise without distorting the original speech signal

#### • 思路

- Use a **feedforward neural network with one hidden layer** as a nonlinear predictive filter.
- The hyperbolic tangent functions are used as the nonlinear transfer function of the hidden nodes and the transfer function of the output layer node is linear.
- Apply the Predictive Minimum Description Length (PMDL) principle to determine the optimal number of input and hidden nodes.

#### NPHMM Neural Predictive Hidden Markov Model

#### • 前提

the nonlinear and nonstationarity nature of speech

#### • 思路

- NPHMM is a nonlinear autoregressive process whose time-varying parameters are controlled by a hidden markov chain, speech is the output of a NPHMM.
- Given some speech data for training, the parameter of NPHMM is estimated by a learning algorithm based on the combination of **Baum-Welch algorithm** and a neural network learning algorithm using the **back propagation algorithm**.
- The Extendend Kalman Filter (EKF) technique, involving an autoregressive model for each class, can be used to provide the maximum-likelihood estimation for speech.

#### Denoise Auto Encoder

- 前提
  - DO NOT require any such apriori conditions to be met when applying the enhancement
- 结构
  - Use a deep neural network (DNN) with multiple layers of fully connected neurons
- 目标
  - Estimate the masks that give the desired clean speech spectra after multiplying the noisy spectra (masking)
  - Estimate clean speech spectra directly (mapping)
- 拓展
  - CDAE
    - the use of a convolutional neural network (CNN) as a convolutional denoising autoencoder

### Other NN Based Approaches

- RNPHMM(Recurrent Neural Predictive Hidden Markov Model)
  - The nonlinear prediction model is based on a Recurrent Neural Network
  - The unknown parameters are estimated by a learning algorithm derived from the Baum-Welch and RNN back-propagation algorithms
- Employing time delay neural network for Mel-scaled spectral estimation
- Multi-layer perceptron (MLP) neural network estimate the log spectra of speech
- Dual EKF
  - A neural network based time-domain method removing nonstationary and colored noise from speech.
  - the availability of only the noisy signal