

Enhancement of reverberant Speech using Kurtosis of LP Residual

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April 10, 2010



Outline

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff



Next

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff



Scope and Motivation

- Ideally, speech communication systems use direct signal of a source
- In real life scenarios, major challenges originates from the degradation in capturing speech in a confined space:
 - Background noise
 - Reverberation
 - Other interferences
- Linear Prediction residual is a very good metric of reverberation in speech.



Reverberation

- Reverberation: Presence of delayed and attenuated copies of source signal in the received signal.
- Cause: Reflections from various surfaces in the room.
- Received Signal is the clean speech convolved with the Room Impulse Response (RIR), and added ambient noise:

$$x(n) = s(n) * g(n) + w(n)$$

• Measure: **Reverberation time** (T₆₀): Time required for a sound to drop 60 decibels or to decay to a value one millionth of its original intensity.



Acoustic Environment of a Room

Example (The simplest case of single reflective surface)



A typical Room Impulse Response.



t [s]



Next

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff



Dereverberation

Aim To get clean speech out of reverberated signal using deconvolution *(in some sense)*.



Dereverberation

Aim To get clean speech out of reverberated signal using deconvolution (*in some sense*).

Classification

- General Signal \longleftrightarrow Speech Signal
- Based on Enhancement: Human Perception ↔ Automatic Speech Recognition (ASR)
- Single Channel \longleftrightarrow Multi-Channel



Approaches

General Signal

No a priori knowledge about the signal.

Speech Signal

Various properties of speech and language can be utilized, such as: voiced/unvoiced speech, harmonic structure, Model of speech production, *etc.*



Approaches

For Better Human Perception

- Improve intelligibility
- Try to get a nicer, nearer sound.
- Rather leave some reverberation than causing spectral distortion
- Application: Hands-free Telecommunication



Approaches

For Better Human Perception

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For Better ASR:

- Get rid to as much reflections as possible.
- A nice sound, in terms of human perception, is not aspired.



Linear Prediction and residual

- Source-Filter Speech Production AR Model:
 - Excitation source (Glottal Pulse train, noise)
 - Vocal Tract (Modelled as an All-pole filter by linear prediction)
- Speech Signal, $s(n) = u(n) \sum_{k=1}^{l} h(k)s(n-k)$
- Predicted Signal, $\tilde{s}(n) = \sum_{k=1}^{l} a(k) s(n-k)$
- LP residual, $e(n) = s(n) \tilde{s}(n)$
- If speech signal were to be truly the response of an all-pole model → exact predictability at all instants except the excitation instant, *i.e.*,

$$e(n) = u(n)$$
; For $a(n) = h(n)$

• Hence, LP residual essentially represents the excitation signal for voiced speech.



Linear Prediction and Reverberation

- Reverberation mainly affects the excitation signal \Rightarrow LP residual
- Many different approaches to manipulate the LP residual.
 - Apply an adaptive weight function to the LP-residual, [5]. (emphasizes regions with high signal-to-reverberation ratio.)
 - Apply a Code Excited Linear Prediction (CELP) post-filter to the LP-residual.
 - Exploit the higher order statistical properties of LP-residual, e.g., Kurtosis [2, 4].



Next

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff



Maximum Kurtosis based Adaptive Filtering: An Overview

- Control the LMS-like adaptive filter by the "Kurtosis" of the LP residual
- Make use of *a priori* knowledge that the signal to be used is Speech.
- Speech Enhancement for human perception (useful for applications related to hearing aids).
- Single/Multi-channel implementation
- Exploits the properties of cumulants, and speech: Higher order statistics of a Gaussian distribution are zero, hence removes the Gaussian Noise.



What is Kurtosis?

- Etymological meaning: Bulging
- A measure of the "peakedness" of the probability distribution of a real-valued random variable.

$$\Gamma = \frac{\kappa_4}{\kappa_2^2} = \frac{\mu_4}{\sigma^4} - 3$$
 (1)

where:

- $\kappa_n :=$ n-th cumulant
- $\mu_n :=$ n-th central moment, $:= E[(X \mu)^n]$
- $\sigma :=$ second central moment (= std. div.)
- Kurtosis of the normal distribution is 3; 3 is subtracted for normalization.
- Note that cumulants show linear behaviour.



a priori knowledge!

- For clean voiced speech, LP residuals have strong peaks corresponding to glottal pulses.
- For reverberated speech, such peaks are spread in time.
- Implying that, Kurtosis of LP residuals reduces as reverberation increases.
- It has been empirically proved that the Kurtosis of LP residual is a reasonable reverberation metric, [2].



Kurtosis of LP residual: Some results



Simulated Room Environment with following details: $4 \times 13 \times 4 \ m^3$ Mic: Fixed at [2, 2, 2] Source: Moving from [2, 3, 2] to [2, 12, 2] (10 points) Reverberation time: $T_{60} = 0.4$ seconds Note: Identical results if source is fixed and mic is moving.



Implementation - 1

• Develop online adaptive gradient ascent algorithm, that maximizes the LP residual kurtosis.



• Issue: Only valid under the assumption that the LP-coefficients are unaffected by the multipath effects of the room (Holds only in spatially averaged sense).



Implementation - Final

 Reliance on the assumption is removed by using an additional filter with identical coefficients.





Feedback Function

Cost function = Kurtosis of Residual

$$J(n) = \frac{E[\tilde{y}^4(n)]}{E^2[\tilde{y}^2(n)]} - 3$$
(2)

Differential of Cost function

$$\frac{\delta J}{\delta \vec{\mathbf{h}}} = \left(\frac{\left(E[\tilde{y}^2]y^2 - E[\tilde{y}^4]\right)\tilde{y}}{E^3[\tilde{y}^2]}\right)\tilde{\mathbf{x}} = f(n)\tilde{\mathbf{x}}(n)$$
(3)

Feedback function

$$f(n) = \left(\frac{\left(E[\tilde{y}^2]y^2 - E[\tilde{y}^4]\right)\tilde{y}}{E^3[\tilde{y}^2]}\right)$$
(4)



Update Equation

• For single channel implementation:

$$\vec{\mathbf{h}}(n+1) = \vec{\mathbf{h}}(n) + \mu f(n) \tilde{\mathbf{x}}(n)$$
(5)

• For multi channel implementation:

$$\vec{\mathbf{h}}_c(n+1) = \vec{\mathbf{h}}_c(n) + \mu f(n) \tilde{\mathbf{x}}_c(n)$$
(6)

Each channel is independently adapted using the same feedback function.

• $E[\tilde{y}^2(n)]$ and $E[\tilde{y}^4(n)]$ are estimated recursively:

$$E[\tilde{y}^{2}(n)] = \beta E[\tilde{y}^{2}(n-1)] + (1-\beta)\tilde{y}^{2}(n)$$
(7)

$$E[\tilde{y}^{4}(n)] = \beta E[\tilde{y}^{4}(n-1)] + (1-\beta)\tilde{y}^{4}(n)$$
(8)



Experiments and Results

Case 1: Clean Speech $F_s = 8000$ Hz; Room: Dim: 4 \times 4 \times 4 m^3 ; Mic: [2,3,2], Src: [2,2,2]; T_{60} =0.7 Sec



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Waveform - Matlab



Skeleton	Introduction	Dereverberation	Maximum Kurtosis based Adaptive Filtering	Conclusions and Future Work	References Li
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Waveform - Wavesurfer



Skeleton Introduction Dereverberation Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References Li

Spectrogram



Skeleton	Introduction	Dereverberation	Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References	Li
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Case 2: Blind Dereverberation. No info about Room or Clean Speech. $F_s = 16000$ Hz;



Skeleton	Introduction	Dereverberation	Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References	Li
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Waveform - Matlab



Skeleton Introduction Dereverbaration Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References Li

Spectrogram







Case 3: Blind online Dereverberation. No info about Room. $F_s = 8000$ Hz, Room Impulse response taken from AIR databese, Aachen University, Germany [3]



Skeleton	Introduction	Dereverberation	Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References	Li
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Waveform - Matlab



Skeleton Introduction Dereverberation Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References Li

Next

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff



Conclusions and Future Work

- Kurtosis of LP residual is an effective measure of reverberation in speech.
- Significant improvement in reverberated speech was noticed.
- However, does NOT work very well with unvoiced discontinuities in speech.

Future Work

- Authors in [1] claims that an average over several spatially distributed microphones can provide potentially better results.
- Time domain implementation is prone to slow or no convergence because of all variance in the eigenvectors of autocorrelation matrices of the input signal.
- A subband adaptive method is promoted in [2] which is more robust to noise.

Skeleton Introduction Dereverberation Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work References L 0 00 0000 000 000 000 000 0000 000

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Next

Introduction

Scope and Motivation Basics

Dereverberation

Approaches Reverberation and LP residual

Maximum Kurtosis based Adaptive Filtering

Theory Implementation Results

Conclusions and Future Work

Listen to some good stuff

Skeleton	Introduction	Dereverberation	Maximum Kurtosis based Adaptive Filtering Conclusions and Future Work Reference	s Li
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Thank You!



Cumulants

• The cumulants k_n of a random variable X are defined by the cumulant generating function, which is logarithm of the moment-generating function.

•
$$g(t) = log(E[e^{tX}]) = \sum_{n=1}^{\infty} \kappa_n \frac{t^n}{n!} = \mu t + \sigma^2 \frac{t^2}{2} + \dots$$

• Cumulants are then given by derivatives at zero of g(t).

•
$$k_1 = \mu = g'(0)$$