ABSTRACT
Reverberation is damaging to both the quality and the intelligibility of a speech signal. We propose a novel single-channel method of dereverberation based on a linear filter in the Short Time Fourier Transform domain. Each enhanced frame is constructed from a linear sum of nearby frames based on the channel impulse response. The results show that the method can resolve any reverberant signal with knowledge of the impulse response to a non-reverberant signal.

Index Terms— dereverberation, inverse channel filtering, speech enhancement

1. INTRODUCTION
Speech is inherently non-stationary, therefore speech processing algorithms are frequently applied to short frames in which the speech is quasi-stationary. Furthermore, speech is sparse in the time-frequency domain, allowing us to distinguish and enhance the speech content well. Therefore the Short Time Fourier Transform (STFT) domain is the domain of choice for many speech and audio based algorithms.

Reverberation occurs from multi-path propagation of an acoustic signal, \( s[n] \), through a channel with impulse response \( h[n] \) to a microphone. Reverberation causes speech to sound distant and spectrally distorted which reduces intelligibility [1]. The further the source from the microphone the greater the effects of reverberation. Automatic speech recognition is severely hindered by reverberation [2, 3]. Beamformers utilise the time difference of arrival to each sensor in an array to spatially filter a sound field. Due to the multi-path propagation, beamformers fail in reverberant environments. Therefore channel inversion methods are of high importance in spatial filtering fields.

There already exists several dereverberation algorithms in the STFT domain. For example spectral subtraction has been used to estimate the power spectrum of the late reverberation and subtract this from the current spectrum to leave the direct path, [4]; this approach was extended in [5] to introduce the frequency dependence of the reverberation time.

Other methods of dereverberation exist which utilise knowledge of the system impulse response, \( h[n] \), however now exist in the STFT domain. Least squares has previously been used to create an inverse filter from knowledge of the impulse response. [6]. This was extended into the multichannel domain with the Multiple-input/output INverse Theorem (MINT), [7], which is capable of finding exact inverse filters, through the use of multiple transmission channels.

We wish to create an algorithm in the STFT domain which utilises knowledge of the impulse response, \( h[n] \), for the uses of dereverberation. However simply creating an inverse filter in the STFT domain is not straightforward, as the STFT process is time-variant. We present a single-channel method of dereverberation based on a linear filter which combines nearby frames which uses a novel method to account for the time varying nature of the STFT domain. The frames are linearly combined using coefficients computed through a least squares based method on the impulse response.

The remainder of the paper is as follows. In Section 2 the method is outlined. Section 3 details the process to select the optimal coefficients for dereverberation. The results of the algorithm are detailed in Section 4 and conclusions are drawn in Section 5.

2. STFT-DOMAIN DEREVERBERATION
The observed reverberant signal, \( y[n] \), at the microphone is the convolution of the source signal, \( s[n] \), and the channel impulse response, \( h[n] \):

\[
y[n] = \sum_{m=0}^{M-1} h[m]s[n-m]. \tag{1}
\]

Exploiting knowledge of the channel impulse response, we propose a new method to reduce the effects of reverberation on \( y[n] \), to form an estimate, \( \hat{s}[n] \), of the original signal.

The reverberant signal is transformed into the STFT domain using a window, \( w[n] \) and an overlapping factor \( Q \):

\[
Y_k[l] = \sum_{n=0}^{QR-1} y[n + lR]w[n]e^{-j2\pi \frac{kn}{QR}}, \tag{2}
\]

where \( l \) represents the frame number, \( k \) the frequency bin and \( R \) the frame increment. The enhanced signal is formed through a linear sum of nearby frames of the reverberant sig-
nal:
\[ \tilde{S}_k[l] = \sum_{r=-A}^{B} G_k[r] Y_k[l - r], \quad (3) \]

where \( A \) is the number of future frames and \( B \) is the number of past frames to be used in the enhancement. The resulting frames are then transferred back into time frames with the inverse Discrete Fourier Transform (DFT):
\[ \hat{s}[l, m] = \frac{1}{QR} \sum_{k=0}^{QR-1} \tilde{S}_k[l] e^{j2\pi \frac{km}{QR}}, \quad (4) \]

which are then overlap-added \[8\] to form the enhanced time signal:
\[ \hat{s}[n] = \sum_{l=n-Q+1}^{n+l} \hat{s}[l, n-lR] w[n-lR]. \quad (5) \]

where \( l_n = \lfloor \frac{n}{R} \rfloor \). Perfect reconstruction, \( \hat{s}[n] = y[n] \), is obtained with the coefficients \( G_k[r] = \delta[r] \) provided that the window used for analysis and synthesis satisfies:
\[ \sum_{q=0}^{QR-1} w^2[qR + n] = 1 \quad \forall n \in [0, R - 1] . \]

3. OPTIMAL COEFFICIENTS

Assuming that \( h[n] \) is known, our goal is to determine the filter coefficients \( G_k = [G_k[-A] \ldots G_k[B]]^T \) so that \( \hat{s}[n] \approx s[n] \).

Consider the response of (3) when the input signal is an impulse at sample \( \lambda \):
\[ s^{(\lambda)}[n] = \delta[n - \lambda], \quad \lambda \in [0, R - 1] . \]

When processing in the STFT domain, the earliest output frame that is affected by the impulse occurs at \( l_{\text{min}} = 1 - Q - A \), whereas the latest frame affected is \( l_{\text{max}} = 1 + B + \lfloor \frac{M+\lambda-2}{R} \rfloor \). Applying the process from (3) we can find a relationship between the channel STFT of the impulse response, \( H_{\lambda}[l, k] \), and the desired impulse response \( H_{\lambda}[l, k] \), which is the STFT of the direct path impulse response, when there are no reflections present.

We determine \( G_k \) to minimise the difference between the two. So for each frequency bin, \( k \), we have an overdetermined set of equations:
\[ \tilde{H}^{(\lambda)}[l, k; G_k] = \sum_{r=A}^{B} G_k[r] H^{(\lambda)}[l - r, k] \approx \tilde{H}^{(\lambda)}[l, k], \quad (6) \]

for each \( \lambda = [0 : R - 1] \) and \( l = [l_{\text{min}} : l_{\text{max}}] \). This gives us \( (2 + A + B + Q) R + M - 1 \) equations, with \( A + B + 1 \) unknowns. This process is shown in Fig. 1. We combine \( B \) past frames with \( A \) future frames to best approximate the current frame from the desired impulse response.

We solve these equations using linear least squares, \[9\], to find:
\[ G_k = \arg \min_{G_k} R \sum_{\lambda=0}^{R-1} \sum_{l=l_{\text{min}}}^{l_{\text{max}}} \left( \tilde{H}^{(\lambda)}[l, k; G_k] - \tilde{H}^{(\lambda)}[l, k] \right)^2. \]

The overall impulse response of the computed channel is time-variant but we can determine an average channel response as the inverse STFT of:
\[ \hat{H}[l, k] = \frac{1}{R} \sum_{\lambda=0}^{R-1} \tilde{H}^{(\lambda)}[l, k; G_k] \exp \left( 2\pi \frac{k}{QR} \right), \quad (8) \]

where a phase shift is applied to correspond with the sample position within the frame.

3.1. Time domain error bound

The above minimisation problem minimises the reverberation present in the enhanced signal. Let us define the error in the impulse responses in both the time domain and the STFT domain as:
\[ h_e[n] = \tilde{h}[n] - \hat{h}[n] . \]

The error in a single frame in the STFT domain is as follows:
\[ H_{e, k}[l] = \tilde{H}^{(\lambda)}[l, k] - \tilde{H}^{(\lambda)}[l, k]. \]

The total power of the error in the STFT domain across all frames, frequencies and shifts is denoted:
\[ P_f[n] = \frac{1}{QR} \sum_{k=0}^{QR-1} \sum_{\lambda=0}^{R-1} \sum_{l=l_{\text{min}}}^{l_{\text{max}}} |H_e[l, k]|^2 . \]

Using Parseval’s theorem, the power of the error in the time domain is given as:
\[ \sum_{n=0}^{QR-1} |h_e[n]|^2 = \frac{1}{QR} \sum_{k=0}^{QR-1} \sum_{\lambda=0}^{R-1} \sum_{l=l_{\text{min}}}^{l_{\text{max}}} |H_e[l, k]|^2 . \]
Alternatively we can express the error power, in the time domain, as the weighted sum of the frames with the window function:

\[ h_e[lR + n] = \sum_{q=0}^{Q-1} w[qR + n]h_e[qR + n, l - q]. \]

We sum over all time samples to give the total error:

\[ \sum_{l=0}^{R-1} \sum_{n=0}^{N-1} \left( \sum_{q=0}^{Q-1} w[qR + n]h_e[qR + n, l - q] \right)^2 = (10) \]

Thus applying the Cauchy Schwatz inequality to (9) and (10), we can show that the error in the STFT domain is an upper bound for the time domain error:

\[ \sum_{l=0}^{R-1} \sum_{n=0}^{N-1} \left( \sum_{q=0}^{Q-1} w[qR + n]h_e[qR + n, l - q] \right)^2 \leq \frac{1}{QR} \sum_{k=0}^{QR} \sum_{\lambda=0}^{QR-1} \sum_{l=0}^{QR-1} |H_e[l,k]|^2. \]

Therefore solving the related problem in the STFT domain places an upper bound on the amount of reverberation in our output signal.

4. EVALUATION

To evaluate the reduction in reverberation, we use two metrics: the Direct-to-Reverberant Ratio (DRR) [10] and the Signal-to-Reverberation Ratio (SRR) [11]. To evaluate the perceptual quality of the enhanced signals Perceptual Evaluation Of Speech Quality (PESQ), [12], is used. The DRR [dB] is defined as follows:

\[ \text{DRR} = \frac{10}{R} \log_{10} \left\{ \frac{E_d(\lambda)}{(\sum_n |H[n]|_2^2)} \right\} \]

where \( E_d(\lambda) \) is the direct path energy. The direct path in the impulse response may occur in between samples, therefore the path energy will be spread across the nearby samples with a sinc function. Thus the direct path energy is computed using a convolution with a sinc function with a varying offset until a maximum is found:

\[ E_d(\lambda) = \max_\sigma \sum_{n=-\eta}^{\eta} \left( \frac{\sin(\pi(n + \sigma)}{\pi(n + \sigma)} \right) |\lambda[n_n + n_d]|^2, \]

where \( n_d \) is the nearest index of the direct path in the impulse response, \( \eta = 8 \) is the number of sidelobes of the sinc function to use in the summation and \( \sigma = [-1 : 1] \) is the offset that finds the maximum power.

The SRR [dB] is defined on a frame by frame basis and then averaged across the whole signal:

\[ \text{SRR}_{\text{seg}} = \frac{10}{M} \sum_{k=0}^{M-1} \log_{10} \left\{ \frac{\sum_{n=kR}^{kR+QR-1} |s_d[n]|^2}{\sum_{n=kR}^{kR+QR-1} (s_d[n] - \hat{s}[n])^2} \right\}, \]

where \( M \) is the total number of frames, \( s_d[n] \) represents the original direct path signal and \( \hat{s}[n] \) is the enhanced signal. It gives a measure of the reverberation power in relation to the useful direct path. It is a similar measure to the DRR but uses speech signals rather than the channel response.

The optimal coefficients from Section [3] were calculated for a Room Impulse Response (RIR) and the corresponding channel response from [6] was found. A total of 600 RIRs were used to test the system. These correspond to a single source and microphone in 40 different rooms and 15 different position combinations in each. The impulse responses were generated using the Room Impulse Response Generator from [13], which is based on the image method [14]. In all cases \( Q = 4, R = 64, A = 9, B = 9 \).

As both the SRR and PESQ work on speech samples the TIMIT core test set [15] was chosen. Each speech sample was convolved with each \( h[n] \) before undergoing enhancement as described in [3]. The before and after signals, \( y[n] \) and \( \hat{s}[n] \), were then used with the SRR and PESQ metrics to gauge any improvement.

The performance of the proposed algorithm has been compared to the time domain inverse filter as proposed by Widrow, [6]. The method designs an inverse filter, \( g[n] \), through least squares to best invert the system response, \( h[n] \), [7].

\[ \begin{bmatrix} h[0] \\ \vdots \\ h[N_h - 1] \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} \vdots \\ h[0] \\ \vdots \\ h[N_h - 1] \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} g[0] \\ g[1] \\ \vdots \\ g[M - 1] \end{bmatrix}^T, \]

where \( N_h = 1024 \) in our case.

4.1. Results

The DRR was computed for both \( h[n] \) and \( \hat{h}[n] \) across all 600 RIRs. The results comparing the DRR before and after the algorithm are shown in Fig. 2. The DRR improved for all the impulse responses tested except those where the original DRR exceed 0 dB. The resulting performance is independent of the amount of reverberation in the initial signal and hovers close to 6 dB, giving an improvement of up to 34 dB. Thus the algorithm is able to reduce reverberation to the same level regardless of how reverberant the original channel is.
The averaged SRR for each RIR is shown in Fig. 3. It follows a similar pattern to the DRR. The enhanced signals hover around 0 dB. When the original SRR surpassed 0 dB, the algorithm was unable to make any further improvements, and caused slight degradation to these non-reverberant signals.

The enhancement gave a small gain in perceptual quality which, whilst it does not show the removal of reverberation, does show that the algorithm does not introduce significant distortion. Due to the limited improvement in the perceived speech quality the algorithm has good uses in approaches which require signals without reverberation, rather than end user perceptual improvements.

Samples of the reverberant and processed speech are available on the internet: [16].

5. CONCLUSIONS

We have described a novel approach to dereverberation using a linear filter in the STFT domain. Using knowledge of the channel impulse response we can find an optimal combination of frames to reduce the effects of reverberation. The algorithm gives clear performance gains in dereverberation. Both the DRR and the SRR show that regardless of the amount of initial reverberation present, the enhanced signal has a similar low level of reverberation present, whilst not introducing distortion.

We have shown that the proposed STFT domain algorithm is as good as the time domain inverse filter; allowing us to apply dereverberation in the more appropriate domain without loss of performance.

We have overcome the time-variance of the STFT by considering all the possible impulse positions within a single frame.

By working in the STFT domain we can solve each frequency band, $k$, independently. The above give a useful framework that suits many applications already processing in this domain.
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