CLCNET: DEEP LEARNING-BASED NOISE REDUCTION FOR HEARING AIDS USING COMPLEX LINEAR CODING

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ABSTRACT

Noise reduction is an important part of modern hearing aids and is included in most commercially available devices. Deep learning-based state-of-the-art algorithms, however, either do not consider real-time and frequency resolution constrains or result in poor quality under very noisy conditions.

To improve monaural speech enhancement in noisy environments, we propose CLCNet, a framework based on complex valued linear coding. First, we define complex linear coding (CLC) motivated by linear predictive coding (LPC) that is applied in the complex frequency domain. Second, we propose a framework that incorporates complex spectrogram input and coefficient output. Third, we define a parametric normalization for complex valued spectrograms that complies with low-latency and on-line processing.

Our CLCNet was evaluated on a mixture of the EUROM database and a real-world noise dataset recorded with hearing aids and compared to traditional real-valued Wiener-Filter gains.

Index Terms— noise reduction, speech enhancement, LPC, hearing aid signal processing, deep learning

1. INTRODUCTION

Noise reduction is an emerging field in speech applications and signal processing. Especially in the context of an aging society with an increase in spread of hearing loss, noise reduction becomes a fundamental feature for the hearing-impaired.

Advances in deep learning recently improved the performance of noise reduction algorithms [1, 2, 3]. It is common practice to transform the noisy time-domain signal into a time-frequency representation, for instance using a short-time Fourier transform (STFT). Usually, only the magnitude of the complex valued spectrogram [1, 4] is used for noise reduction. Recent publications though, also focus on incorporating phase information in the reconstructed output by using the phase [5] or the raw complex valued spectrogram [6] as input. Most approaches, however, work with high frequency resolution (high-res) spectrograms [7, 6]. This exceedingly simplifies the noise reduction process, since a single scalar value per frequency bin is sufficient to attenuate a narrow frequency range. A low-res spectrogram on the other hand cannot resolve speech harmonics that have a typical distance of 50 Hz to 400 Hz. Hence, a scalar factor is not able to reduce the noise between the harmonics while persevering the speech. Although a single complex factor could be used to perfectly reconstruct the clean signal via the complex ideal ratio mask (cIRM), it is hard to learn [7, 6]. Due to a superposition of multiple, quasi static signals within one frequency bin, not only the phase changes over time but also the magnitude as a result of cancellation. Thus, low-res spectrograms limit the effectiveness of standard complex valued processing methods that mainly bring phase improvement [5, 8].

While other work uses the whole signal in an off-line processing fashion as input for the noise reduction [9, 10, 11], our work requires real-time capabilities. Both high-res spectrograms and off-line processing are not feasible for hearing aid applications, where the overall latency is a very important property. The superposition of both signals results in a clearly audible comb filter effect that is generating a tonal sound impression especially of background noises. Therefore, an overall latency of 10 ms is typically the maximum of what is acceptable [12]. Since higher frequency resolutions introduce bigger delays [13], noise reduction for hearing aids needs to be performed on low-res spectrograms. This, and on-line processing constraints are not considered in any state-of-the-art (SOTA) algorithms.

To overcome these limitations, this study proposes a framework motivated by LPC. Due to the low resolution, one frequency band can contain multiple harmonics. This results in a superposition of multiple complex valued periodic signals for each frequency band. LPC is able to perfectly model a superposition of multiple sinusoidals given enough coefficients. Due to this property, LPC finds a use case in speech coding and synthesis [14]. Yet, it is often only applied on time-domain signals as a post-processing step. Instead, we propose a complex valued linear combination of the model output and the noisy spectrogram. We can show that this outperforms previous approaches like real valued Wiener-Filter (WF) masking on low-res spectrograms.

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2. RELATED WORK

Removing unwanted environmental background noise in speech signals is a common step in speech processing applications. Complex valued neural networks as well as phase estimation have been of great interest in speech enhancement lately, since the perceptual audio quality has been reported to be improved significantly [5, 7, 6, 10].

One approach is to estimate magnitude and phase or a phase representation either directly [5] or use the estimated magnitude and noisy phase to predict the clean phase [8]. Estimating the clean phase directly, however, is quite hard, because of its spontaneous, random-like nature. Zheng et al. [5] jointly estimated the magnitude spectrogram and a phase representation based on the time derivative of the phase. Le Roux et al. [8] estimated a magnitude mask and clean phase using a cookbook-based method. Reducing the phase estimate from a continuous space to discrete cookbook values reduces the search space and allows to use output activations that are designed to represent the cookbook values, like a convex softmax.

Other work focuses on estimating a complex valued mask. Williamson et al. [7] used a complex ratio mask (CRM) to reconstruct a clean speech spectrogram. Yet the network did not use complex valued input features, but used traditional real valued features such as MFCCs as input. Tan et al. tried to directly estimate the complex valued spectrogram [6] using a linear output layer. This, however, might not be very robust, since the network is allowed to output any value.

None of those SOTA algorithms, however, fulfill the latency and thus low-res spectrogram requirements. Even Tan et al. [4], who propose a convolutional recurrent network for real-time speech enhancement do not specify overall latency. However, the windowing used in their approach for the frequency transform results in 20 ms of delay. Furthermore, it was only evaluated on synthetic noise.

Only Aubreville et al. [1] fully respects those constraints. Their approach uses Wiener-Filter (WF) gains to reduce unwanted environmental noise. The real-valued WF gains can only modify the magnitude of the enhancement spectrogram. This, however, performs poor on low signal to noise ratios (SNRs) since the WF is restricted by frequency resolution, resulting in phase distortions that decrease perceptual quality.

3. COMPLEX LINEAR CODING

In this section, we will describe details of our approach and provide a theoretical motivation. Starting with complex valued LPC, we derive a more general noise reduction framework based on a complex valued linear combination. Finally, we introduce a phase-aware, parametric normalization method for complex spectrograms. We provide details of our implementation, which is qualified to be embedded into a hearing aid signal processing chain, and the used database.

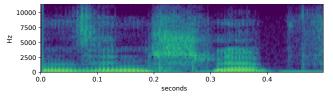


Fig. 1. A power spectrogram using the deployed filter bank from a clean speech sample of the train set. This filter bank is similar to a 96 point STFT. The speech-typical harmonics are not clearly visible due to the low frequency resolution.

3.1. Linear Predictive Coding

Linear predictive coding is known to be a suitable model of the vocal tract response [15] and is still used in SOTA approaches for speech coding and synthesis [14]. Given a signal x_k at sample k, LPC can be described as the linear combination

$$\hat{x}_k = \sum_{i=1}^N a_i x_{k-i} ,$$
 (1)

where a_i are the LPC coefficients of order N and \hat{x}_k is the predicted sample at position k. Let d_k be the prediction error

$$d_k = x_k - \hat{x}_k = x_k - \sum_{i=1}^N a_i x_{k-i} .$$
 (2)

The optimal coefficients a_i can then be found by minimizing the expectation value $E\{d_k^2\}$. This results in n equations that need to be solved. In practice, a solution can be found e.g. via autocorrelation of x and the Levinson-Durbin [16] algorithm. Higher order n allow to model a higher number of superimposed frequencies in the signal x. For instance, Makhoul et al. [15] showed that n = 10 coefficients are enough to sufficiently model the dominant frequencies of the vocal tract.

Although LPC is often only applied to real-valued timedomain signals, it is equivalent for a complex valued signal. In the next section, we describe our proposed noise reduction framework using a general form of equation (1).

3.2. Noise reduction via complex linear combination

Spectrograms have a periodic structure if the underlying time domain signal is a superposition of sinusoidals and the frequency resolution of the spectrogram cannot resolve the different frequencies in the signal. This is caused by cancellation within each frequency band. Since those spectrograms have wide frequency bands, multiple harmonics of human speech can lie within a frequency band. Due to the overlap between two successive windows during STFT, the phase of the different frequencies in the time-domain signals changes with different rotation speed. This may lead to partial cancellation, i.e. the magnitude of the superposition of those frequencies may decrease. This effect can be observed in Fig. 1. Here, a single frequency band is approximately 500 Hz wide. Assuming a minimal human fundamental frequency $f_0 = 100$, up to 5 harmonic oscillations can be captured within a band. To enhance a noisy spectrogram, a naive approach would be to calculate the LPC coefficients of the ideal clean speech via Levinson-Durbin and apply it to the noisy spectrogram. A deep learning-based model would learn the mapping from a noisy spectrogram to the ideal LPC coefficients. This however, does not work very well. First of all, the coefficients computed from the clean spectrogram are only meaningful for time-frequency (TF) bins that include harmonic parts of speech. For TF bins without speech, the LPC coefficients will not enhance the resulting spectrogram. Furthermore, the "ideal" LPC coefficients only slightly reduce white noise and do not enhance the noisy spectrogram w.r.t. any metric, i.e. amplitude (IAM) or energy (WF).

Instead we propose a complex linear coding (CLC) framework. Since we know that LPC modeled by a complex linear combination works well for for harmonic signals like speech, we embed the linear combination as a known operator [17] in the network. Given a noisy spectrogram, the model predicts complex valued coefficient that are applied to the noisy spectrogram again. Thus, CLC will output an enhanced spectrogram that can be transformed into time-domain. The loss can then be computed in either time or frequency domain.

In contrast to LPC, for CLC we can use information of the current and even future frames resulting in a more general form of the linear combination in (1):

$$\hat{\boldsymbol{S}}(k,f) = \sum_{i=0}^{N} \boldsymbol{A}(k,i,f) \cdot \boldsymbol{X}(k-i+l,f) , \qquad (3)$$

were l is an offset and N the order of the linear combination. A(k, i, f) are the output coefficients with i = 0, ..., N for each time-index k and frequency-index f. For l = -1, this is equivalent to LPC. Note that S, A and X are complex, thus the multiplication needs to be complex valued.

As described above, one frequency bin can include up to 5 speech harmonics. Thus, we chose a CLC order of N = 5 for our noise reduction framework.

3.3. Parametric unit norm normalization

Normalization is an essential part of most deep learning pipelines which helps for robustness and generalization. In speech processing applications, most normalization methods are performed on power-spectrogram level which is not applicable for complex valued input. Instead, we propose a bin-wise and phase-sensitive normalization scheme based on the unit norm. Given a filter bank representation X(k, f), the signal is normalized as:

$$\boldsymbol{X}_{\text{norm}}(k,f) = \frac{\boldsymbol{X}(k,f)}{\mu_{k,f}} \cdot \gamma_f , \qquad (4)$$

where μ is the mean of $|\mathbf{X}|$ and $\gamma_f \in \mathbb{R}$ a learnable parameter for each frequency bin. μ can be computed in a realtime capable fashion like a exponential moving average or a window-based approach. Since the complex valued input is only multiplied with scalar values, the phase of \mathbf{X} does not change.

3.4. Hearing aid signal processing chain

Instead of a usual STFT, our signal processing chain employs a standard uniform polyphase filter bank for hearing aids [13]. In particular, a 48-frequency-bin analysis filter bank transforms the time-domain signal of clean speech s, noise n and noisy mixture m into the representations S(k, f), N(k, f), M(k, f).

We directly feed the complex valued filter bank representations into a parametric channel-wise normalization to enhance the weaker frequency bands. After the noise reduction step via complex linear combination (3), the enhanced filter bank representation $\hat{S}(k, f)$ gets synthesized again.

4. EXPERIMENTS

4.1. Dataset and Implementation Details

The clean speech corpus contains 260 German sentences from 52 speakers from the EUROM database [18] upsampled to 24 kHz. We furthermore used 49 real-world noise signals including non-stationary signals to generate noisy mixtures. The noise signals were recorded in various places in Europe using hearing aid microphones in a receiver in a canal-type hearing instrument shell (Signia Pure 312, Sivantos GmbH, Erlangen, Germany) and calibrated recording equipment at a sampling rate of 24 kHz. The mixtures were created with up to 4 noises at various SNRs of $\{-100, -5, 0, 5, 10, 20\}$ dB and level offsets $\{-6, 0, 6\}$ dB sampled online with an uniform distribution. The dataset was split on original signal level into train, validation and test sets, where validation set was used for model selection and test set to report the results.

Our framework was implemented in PyTorch [19] using a similar MLP-based architecture (3 fully connected layers with ReLU activations) and temporal context to [1]. Only the input and output layers were modified due to the complex filter bank representation input and coefficient output. Thus, we chose a tanh activation to also allow negative output. The complex input spectrogram is normalized given the temporal context of $\tau = \tau_1 + 1 + \tau_2$, where $\tau_1 = 200 \text{ ms}$ is the look-back and $\tau_2 = 2 \text{ ms}$ the lookahead context. We used an Adam optimizer with an initial learning rate of $3 \cdot 10^{-4}$. The loss was computed in time-domain using a multi-objective loss of RMSE loss and scale-invariant signal distortion ratio

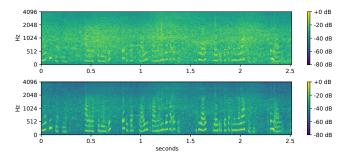


Fig. 2. High resolution Mel spectrograms of a noisy input and an enhanced output.

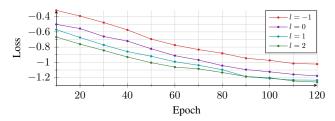


Fig. 3. Validation loss for different offsets l. An offset of l = -1 corresponds to predicting the next frame like in LPC.

(SI-SDR) [20]. We found that the SI-SDR helped to enhance higher harmonics of the original speech, while the RMSE loss penalized the RMS difference of the enhanced audio. The scale-dependent SDR did not converge in out experiments.

The maximum attenuation of the noise reduction was limited to 14 dB similar to [1], because in practice not all noise should be removed for hearing aid applications. Since the attenuation cannot be limited afterwards, the model was trained to only improve the SNR by 14 dB. Therefore, the clean speech was not used directly as target but rather a mixture with an Δ SNR_t = 14 dB over the noisy input signal. Fig. 2 shows an utterance of the test set with an SNR of -5 dB, enhanced with an attenuation of Δ SNR_t = 14 dB. German and English audio samples are available at [21].

4.2. Objective Evaluation and Discussion

The enhanced speech signals are evaluated using two objective metrics, namely the scale-invariant signal distortion ratio (SI-SDR) [20] and the difference between noisy and enhanced signal w.r.t. the short-time objective intelligibility (STOI) [22], denoted as Δ STOI. We evaluate different configurations of our framework and compare them with previous work [1].

When comparing the loss for different offsets l as shown in Fig. 3, we can see that the CLC-framework benefits from lookahead context. While an offset of l = -1 leads to a significant performance drop, the loss converges for a higher context as l gets greater than 1. Thus we chose l = 1 for further experiments.

The objective results in table 1 show the performance of different CLCNet configurations. We find that limiting the maximum attenuation $\Delta \text{SNR}_t = 14 \text{ dB}$ decreases SI-SDR especially for low SNRs like -5 dB, which is an expected result. For higher SNRs, however, the difference is negligible.

The strength of complex linear coding is evident for low SNRs like 0 dB to -5 dB. Fig. 4 compares the Δ STOI metric

Table 1. SI-SDR [dB] test set performance for different SNRs.

Offset l	20	10	5	0	-5
	$\Delta SNR_t = 14 dB$				
-1	21.64	15.73	12.27	8.06	3.24
0	21.18	15.69	12.21	8.07	3.14
1	22.27	16.19	12.70	8.53	3.63
2	22.74	16.28	12.58	8.18	3.20
	$\Delta \text{SNR}_t = 100 \text{dB}$				
1	21.69	16.28	13.48	10.09	5.88

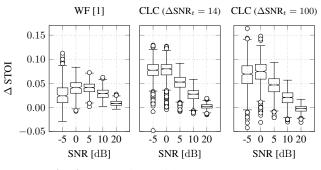


Fig. 4. Comparison with WF-approach [1]

with the WF approach and shows a significant improvement at $-5 \,dB$ and $0 \,dB$. Interestingly, limiting the attenuation via ΔSNR_t to 14 dB yields slightly better results and smaller interquartile range w.r.t. $\Delta STOI$. Due to the 5 coefficients per TF bin, CLC is able to reduce only parts of one frequency band, reducing noise between harmonics, while preserving most of the speech. Fig. 5 shows this effect in comparison with the conventional Wiener-Filter approach.

For high SNRs however, the Wiener-Filter often performs satisfactory. Here, noise between the harmonics only has little impact on the phase, which would impair the listening experience. The WF with its linear mapping between noisy and clean filter bank representation is perfectly suited for these cases. While CLC with $l \ge 0$ could also learn this, it is a lot harder since it needs to zero almost all coefficients and only keep the real part of the coefficient of the current frame. Furthermore, the attenuation of a WF can be modified before being applied to the signal, so a model can be trained without "noisy" input via Δ SNR_t. This allows the network to easily remove all noise for high SNR conditions.

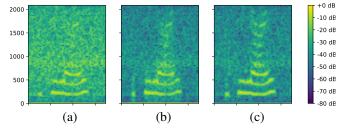


Fig. 5. Detail view of Fig. 2 (7.5 s to 8 s). Noisy input (a), WF [1] (b), CLC (c). CLC is able to reduce the noise between harmonics within a single frequency band, while WF is limited by the frequency band width and thus, can only reduce the noise before and after speech segments.

5. CONCLUSION

In this work we presented a real-time capable noise reduction framework for low resolution spectrograms based on complex linear coding. We showed that our CLC framework is able to reduce noise within individual frequency bands while preserving the speech harmonics. Especially for low SNRs, objective metrics show that CLCNet significantly outperforms previous work.

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