SIDECHAIN HARMONIC ENHANCEMENT OF NOISE CORRUPTED SPEECH FOR HEARING IMPAIRED LISTENERS

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ABSTRACT

This work presents a single channel speech enhancement approach aimed at improving speech clarity for hearing impaired listeners under challenging listening conditions. The proposed method applies nonlinear distortions to speech components isolated from the observed noisy signal using aggressive speech enhancement. The enhanced components are then mixed back into the noisy signal. The results show that the proposed approach significantly improves speech clarity in noise.

Index Terms— speech enhancement, speech clarity, harmonic distortion, hearing aids

1. INTRODUCTION

Enhancement of speech corrupted by noise is one of the biggest challenges for the hearing aid industry. One problem shared by conventional noise reduction (NR) algorithms, e.g., [1, 2, 3], is that they do not improve the local signal-to-noise ratio (SNR) within individual time-frequency units. Typically, attenuation is applied to individual time-frequency units according to a continuous gain function based on an estimate of the local SNR. As such, conventional approaches scale both speech and noise components in a given time-frequency unit by the same amount. For this reason, the local SNR within a given unit remains unchanged after processing. Thus, while speech quality or listening comfort may be improved, speech intelligibility is typically degraded, or at best unchanged [4, 5]. Unlike the conventional approaches which focus solely on attenuation of the unwanted noise from the noisy mixture, the focus of the present work is on addition of new speech-related information. The new content is based on spectral regions characterized by high local SNR and is mixed into spectral regions with potentially low local SNR.

In commercial music production, harmonic enhancement (HE) is used frequently as a "sweetening" technique [6]. It is itself a distortion process, and is generally only applied in small amounts, to prevent the "sweetening" from being perceived as objectionable distortion or corruption of the signal [7]. The end goal is to make certain frequency ranges more apparent, clearer, and more "pleasing" to listen to. Typically, harmonics are generated by applying nonlinear distortion to the music, or to the individual vocals or instruments, possibly with band-pass filtering of the signal before and/or after the nonlinearity [8]. The use of nonlinear distortions also finds application in the area of artificial bandwidth extension [9]. For example, speech signals transmitted over public switched telephone networks are band limited to 300–3400 Hz. The bandwidth and quality of band-limited speech signals can be improved through diligent application of nonlinear distortions at the receiving end [9].

While such perceptually desirable effects can be achieved when applying harmonic enhancement to the target material (whether it be speech or music), it is generally undesirable to introduce harmonically related components of the noise (or the mixture). For this reason, the use of harmonic enhancement is typically limited to relatively noise-free signals. In order to overcome this, we propose to apply aggressive speech enhancement (ASE) as a preprocessor to harmonic enhancement. In this way, only the parts of the target-plus-masker mixture strongly dominated by the target speech are subjected to nonlinear distortions. This processing takes place in a sidechain, and the newly generated speech-like information is then added back into the time-frequency units in the main signal path. As such, the proposed approach represents a unique combination of speech enhancement and signal enhancement techniques. In this work, we focus specifically on single channel enhancement of speech corrupted by additive noise at challenging mixture SNRs (i.e., $\leq$5 dB), with the primary objective of improving speech clarity for hearing impaired listeners under such conditions.

The remainder of this work is organized as follows. Details of the proposed algorithm are presented in Section 2. Experiments used for algorithm parameter selection are discussed in Section 3. Section 4 presents speech enhancement experiments used to evaluate the performance of the proposed method in terms of speech clarity and sound quality. Results and discussion are presented in Section 5. Conclusions are given in Section 6.

2. SIDECHAIN HARMONIC ENHANCEMENT

A block diagram of the proposed sidechain harmonic enhancement (SHE) algorithm is given in Fig. 1. The main signal path, along with a sidechain, are shown. In the main path, NR is optionally applied, with its spectral gain function hard limited to $G_{\max}$, i.e., the gain function is permitted to apply at most $G_{\max}$ dB attenuation. Thus, NR is enabled when $G_{\max}$>0, and disabled when $G_{\max}$=0. Only very mild NR is permitted (i.e., $G_{\max}\leq 3$) in order to avoid addition of perceptually-distracting NR-related artifacts and to ensure any unwanted SHE-introduced artifacts are masked.

In the sidechain, the noisy signal is bandlimited at the ASE input to between f_1 and 7500 Hz. Speech-dominated components are then isolated from the bandlimited signal in the ASE block. This can be achieved using binary mask types of approaches, e.g., [10, 11, 12, 13], or by utilizing more traditional speech enhancement methods, e.g., [14, 1, 3, 15], tuned to achieve aggressive noise reduction. HE is then applied in order to generate harmonically-related speech-like components in other parts of the spectrum. For this purpose, a nonlinear transformation can be applied to the time domain signal, e.g., soft-clipping, cubic compression, or half-wave

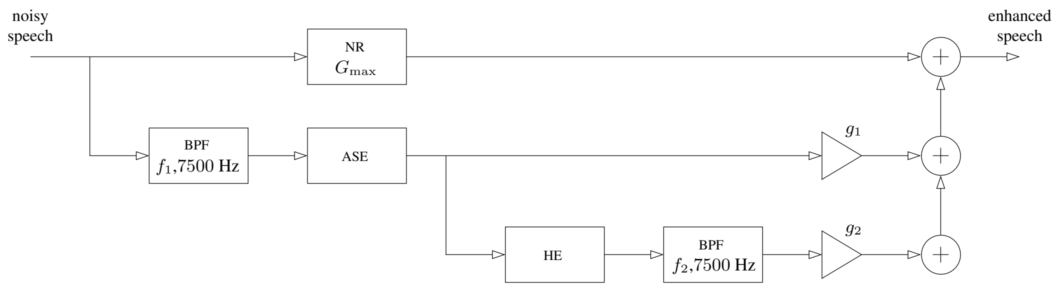

Fig. 1. A block diagram of the proposed algorithm.

rectification. Alternatively, HE could also be achieved directly in the frequency domain, e.g., by frequency transposition. The output signal from HE is then bandlimited to between f_2 and 7500 Hz. The enhanced signal is computed as the sum of this bandlimited signal scaled by g_2, the ASE output signal scaled by g_1, and the main path signal. In the above f_1 and f_2 are tunable frequency parameters, and $G_{\max}$, g_1, and g_2, are tunable gain parameters.

The bandlimiting operations at the input of ASE and at the output of HE serve the following purpose. The former selects the spectral region to be subjected to harmonic enhancement, while the latter selects the range of harmonically enhanced frequencies to be retained for mixing with the main path signal. The output of ASE can also be mixed back in directly with the noisy signal in the main path, with the gains g_1 and g_2 controlling how much of ASE and HE processed signals are added back into the main path. While the former contributes (adds energy) to spectral regions with already high SNR, the latter hopes to contribute new information to low SNR spectral regions.

Our realization of the SHE algorithm utilized a short-time Fourier analysis-modification-synthesis system for frequency domain processing. This system was based on the weighted overlap-add (WOLA) discrete Fourier transform filterbank [16, 17]. The sampling frequency was set to 16 kHz. The WOLA analysis duration was set to 4 ms, with a frame shift of 0.5 ms. The size of the discrete Fourier transform (DFT) in the WOLA analysis was set to 32. The DFT was computed using a fast Fourier transform (FFT) algorithm. The processing was applied in the first sixteen bands. The energy in the Nyquist band was set to zero. Conjugate symmetry of the spectrum was ensured prior to synthesis.

The minimum mean-square error (MMSE) short-time spectral amplitude (STSA) estimator [1], in conjunction with the unbiased noise power estimator proposed in [18], were used for the NR and ASE blocks. The reference implementation given in [19] was utilized within the WOLA-based system. Time constants, used for smoothing of noise power, speech probability and the a priori SNR estimates, were tuned so as to achieve aggressive isolation of speech dominated spectral regions. Time domain half-wave rectification was used for HE.

3. PARAMETER SELECTION EXPERIMENTS

The parameter space for the SHE method proposed in Section 2 was explored by hearing impaired listeners using a genetic algorithm (GA) approach [20]. The GA is a biologically inspired optimization routine that uses the concept of survival of the fittest, in which the best solutions to a problem evolve while poorer solutions die off [20]. A benefit of a GA is that it facilitates exploration of several parameters at once to quickly determine which solutions (parameter sets) produce the best results for the listener. This is especially important in situations in which the parameters may interact with each other, and therefore cannot be optimized individually. Rather than testing all possible combinations of parameter settings, which may be very time consuming, or not at all feasible, a GA explores the complex parameter space in a directed way, reducing the amount of time spent testing regions where the parameter space consistently generates poor solutions. Locally optimal solutions are determined by having a listener compare two sets of parameters, or "genes," from a pool of genes. Genes that are rated poorly eventually die off (i.e., they are removed from the gene pool), whereas genes that the listener rates highly remain in the gene pool and contribute to the future generations of genes. New genes are created when highly-rated genes either mutate (change some of their parameters) or "mate" with other genes to create "child" genes.

The GA approach was chosen for this study, because there were many parameters for which the optimal solutions were unknown. Further, these parameters may interact with each other, and therefore could not be optimized individually. It was also unknown whether the optimal solution(s) would be participant-specific or general to the group. The goal was to identify parameter sets associated with improved speech clarity. The searched parameter space consisted of five variables, discretized as shown in Table 1.

The GA testing consisted of hearing impaired participants (see Section 4.1) listening to pairs of stimuli, and indicating on a discrete scale which of the two stimuli had higher speech clarity and by how much (slightly, moderately or strongly so). For this purpose a GA toolbox given in [21] was utilized.

The results of GA testing are summarized in Table 2. Individual as well as "global" parameter sets are shown. For the former, the fittest parameter set identified for each subject through GA-based listening test is listed. The latter (MILD and STRONG) were computed based on k-means clustering of the fittest parameter sets identified for each subject. The MILD parameter set includes noise reduction in the main signal path with strong harmonic harmonic enhancement

PARAMETER	VALUES
$G_{\max}$	$\{0, 2, 3\}$
g_1	$\{-\infty, -6, 0, 6, 9.5\}$
g_2	$\{-6, 0, 6, 9.5\}$
f_1	$\{250, 750, 1250\}$
f_2	$\{250, 750, 1250, 2500, 3750\}$

Table 1. SHE parameters along with discretized values for the GA tests. The listed values for the gain parameters ($G_{\max}$, g_1, and g_2) are all expressed here in dB, while the frequency parameters (f_1 and f_2) are given in Hz.

Treatments		Parameters				
		Gain (dB)			Freq. (Hz)	
		$G_{\max}$	g_1	g_2	f_1	f_2
Global	Mild	2	-6.0	6.0	750	2500
	Strong	0	6.0	0.0	750	1250
Individual	P01	3	$-\infty$	6.0	1250	250
	P02	0	9.5	6.0	750	750
	P03	3	9.5	-6.0	750	2500
	P04	0	6.0	-6.0	250	3750
	P05	0	9.5	6.0	1250	3750
	P06	3	0.0	-6.0	750	250
	P07	2	6.0	0.0	750	250
	P08	0	-6.0	6.0	750	2500
	P09	2	9.5	6.0	750	250
	P10	3	0.0	0.0	1250	3750

Table 2. SHE parameter sets determined based on GA tests.

gain, g_2, but limited aggressive speech enhancement gain, g_1. On the other hand, the Strong parameter set includes no noise reduction, with strong g_1 gain but little g_2 gain.

4. SPEECH ENHANCEMENT EXPERIMENTS

The performance of the proposed method was evaluated through a series of subjective tests. These tests focused on assessment of speech clarity by hearing impaired listeners [22]. Sound quality was also evaluated. The details of these experiments are given in the reminder of this section.

4.1. Subjects

Ten individuals with symmetrical mild-to-moderately severe sensorineural hearing loss (high-frequency audiometric thresholds $\leq$70 dB HL) participated in this study. Note that this is a common type of hearing loss observed in an aging population. The listeners were paid for their participation.

4.2. Speech and noise materials

Speech materials from the TIMIT corpus [23] were used. These were divided into practice and test sets composed of 30 and 48 sentences, respectively. Both sets were gender balanced, i.e., half of the sentences in each set belonged to female talkers and the rest belonged to male talkers. Each sentence in the test set was spoken by a different talker.

Three maskers were used, namely speech shaped noise (SSN) [24] at 0 and 5 dB mixture SNRs, as well as multi-talker babble [25] and restaurant [26] noises at -5, 0 and 5 dB mixture SNRs.

4.3. Types of stimuli

Four treatment types were investigated:

1. Off—the target+masker mixture (baseline)
2. Individual—individualized SHE treatment, i.e., tailored for each participant
3. Mild—global SHE treatment
4. Strong—global SHE treatment

The latter three treatments were based on GA-derived SHE parameter sets outlined in Section 3.

4.4. Stimuli generation

The stimuli for the different treatment types were created as follows. A portion of a given masker recording was selected at random and mixed-in with a speech recording by keeping the level of the speech constant and adjusting the level of the masker to achieve a desired mixture SNR. A given type of signal processing, associated with a given treatment, was then applied—i.e., Off (no processing) or SHE processing (Individual, Mild or Strong). The stimuli were preprocessed to compensate for each individual's hearing loss. Specifically, separate prescriptions appropriate for the hearing loss in each ear were applied. The prescriptions were based on the e-STAT [27] fitting targets. Note that the e-STAT formula provides a mild amount of compression. Sampling frequency of 16 kHz was used for the processing. The stimuli were then up-sampled to 48 kHz, prior to being stored as two channel audio files with 24 bit pulse-code modulation encoding.

4.5. Experiment procedure

A "rate and rank" test (RRT) was used to assess speech clarity and sound quality. The RRT task allows listeners to directly compare several stimuli in each trial. Specifically, the participants were presented with a horizontal scale split into two sections. The left-hand side indicated that the treatment was considered acceptable on a given dimension, while the right-hand side indicated that the treatment was considered unacceptable on that dimension. The separate scales used to asses speech clarity and sound quality, ranged from "very clear" to "very unclear", and from "very good" to "very poor", respectively. Four symbols were shown above each scale. Each symbol was associated with a stimulus pre-generated as outlined in Section 4.4. The participants could listen (and re-listen) to the stimuli by clicking on the symbols. The stimuli were presented over open circumaural headphones (Sennheiser HD600, Wennebostel, Germany). Each stimulus lasted two to three seconds. The listeners were instructed to rate and rank the stimuli (associated with the four treatments) by dragging the symbols onto the continuous scale using a computer mouse. The ratings, bounded between 0 and 1, were collected for the four stimuli in each trial by the computer software.

The speech clarity and sound quality assessments were completed over two separate sessions. At the start of each session, the participants were familiarized with the task during a short practice set composed of 6 trials. The speech materials for these trials were selected at random from the practice set (see Section 4.2). This was followed by a test that consisted of 48 trials: 2 talker genders $\times$ 2 mixture SNRs (SSN) $\times$ 3 sentences + 2 talker genders $\times$ 3 mixture SNRs $\times$ 2 maskers (babble and restaurant) $\times$ 3 sentences, i.e., each treatment was repeated 3 times for each gender, masker and mixture SNR combination. For each of the 48 trials, a unique sentence spoken by a unique talker was used. All variables (gender, masker and mixture SNR) were randomized across listeners. The treatment to symbol allocations were also randomized across trials and listeners. The listeners were encouraged to take breaks. Each session lasted approximately one hour.

4.6. Statistical model

A 5-factor, hierarchical Bayesian linear model was designed for analysis of the RRT responses. In this model, each factor (gender, masker, mixture SNR, treatment, and participant) was a predictor of the parameters of a latent variable representing the speech clarity or sound quality. This latent variable was modeled as a Gaussian whose mean was a linear combination of contributions from all

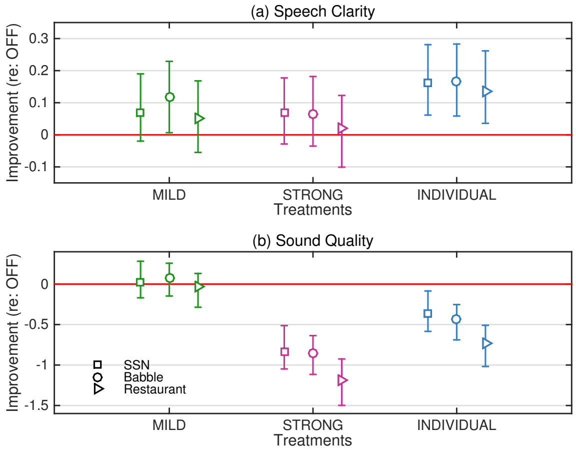

Fig. 2. RRT results in terms of improvements over OFF. Results for speech clarity (top panel) and sound quality (bottom panel) are shown. The results are given for the different treatments and masker types. The results are collapsed across remaining factors. Lack of overlap with the zero line indicates a significant result.

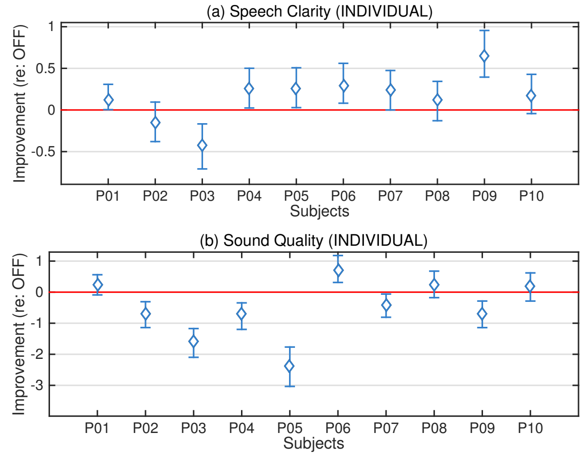

Fig. 3. RRT results given for the INDIVIDUAL treatment, in terms of improvements over OFF, for individual listeners. Results for speech clarity (top panel) and sound quality (bottom panel) are shown. The results are collapsed across remaining factors. Lack of overlap with the zero line indicates a significant result.

factors and all interactions between factors. The participant ratings for each stimulus were mapped from the latent variable space by a logistic function. We further introduced a power function that allowed additional distortion and warping flexibility in that mapping, reflecting the potentially different use of the rating scale by different participants. The parameters of the power function varied only with participant. Finally, the observed ratings were considered noisy observations of the underlying latent variable, and were therefore modeled as normally distributed around the "true" rating. All factors contributing to the latent variable mean (i.e., the main effects and all interactions) were learned by the model, as were the participant-specific power function parameters. Because raw ratings were likely to vary between participants and conditions, effects of treatment were assessed by considering differences in the latent variable mean, between treatments and within conditions. We could then examine these differences in means across and/or within conditions, e.g., we could separately consider the treatment effects across all mixture SNRs and at each individual mixture SNR. Since we were using a Bayesian model, we obtained posterior probability distributions for each of these effects, rather than point estimates. In this way we were able to assess the significance of the result by considering whether the absence of an effect (i.e., difference of zero) was covered by the 95 percent highest density interval of the posterior distribution.

5. RESULTS AND DISCUSSION

The subjective ratings from the RRT experiments presented in Section 4, were analyzed using the hierarchical Bayesian model detailed in Section 4.6. The results, collapsed across participants and mixture SNRs, are summarized in Fig. 2. The top panel shows improvements (re: OFF) in terms of speech clarity, while the bottom panel focuses on sound quality results.

In terms of speech clarity, the individualized treatment showed significant improvements for all of the masker types (SSN, babble and restaurant noise). For the MILD and STRONG treatments, there was a trend toward improved speech clarity, however, this was statistically significant only for the MILD setting with the babble masker.

In terms of sound quality, the STRONG and INDIVIDUAL treatments were rated significantly poorer than no treatment (OFF), while for the MILD treatment, sound quality was maintained, i.e., it did not differ significantly from OFF.

Figure 3 shows results of the RRT tests for individual listeners for the INDIVIDUAL treatment. These can be summarized as follows. Speech clarity was significantly improved over OFF for six participants (P01, P04, P05, P06, P07, and P09). Out of these six subjects, the sound quality: was significantly improved over OFF for one (P06); did not differ significantly from OFF for another (P01); and was significantly degraded from OFF for the other four subjects (P04, P05, P07, and P09).

For two listeners (P08 and P10), neither speech clarity nor sound quality were significantly different from OFF. For one listener (P02), sound quality was significantly degraded from OFF but speech clarity was not significantly affected. For the P03 subject both speech clarity and sound quality were significantly reduced.

The above results show that the GA-based approach was effective at optimizing speech clarity. In some instances, this was associated a degradation in sound quality. For some applications, where maintaining sound quality is an absolute requirement, the GA task could instead be used to optimize the parameters for both speech clarity and sound quality.

Another thing to note is that—for the most part—the global settings, produced based on k-means clustering of the GA results, did not produce significant improvements in speech clarity. One potential reason for this is that the clustering did not incorporate perceptually important weighting for the different parameters.

6. CONCLUSION

In this work, a novel speech enhancement approach was proposed and evaluated on hearing impaired listeners. The processing took place in a sidechain. The method applied nonlinear distortion to speech-dominated content isolated from the noisy mixture using aggressive form of noise reduction. The enhanced components were then mixed back into the main signal path. The results showed that the proposed approach significantly improved speech clarity. For the treatment with the largest clarity improvements, there was also an associated significant reduction in sound quality.

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