SPEECH ENHANCEMENT FOR HEARING-IMPAIRED LISTENERS USING DEEP NEURAL NETWORKS WITH AUDITORY-MODEL BASED FEATURES

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***Abstract*—Speech understanding in adverse acoustic environments is still a major problem for users of hearing-instruments. Recent studies on supervised speech segregation show good promise to alleviate this problem by separating speech-dominated from noise-dominated spectro-temporal regions with estimated time-frequency masks. The current study compared a previously proposed feature set to a novel auditory-model based feature set using a common deep neural network based speech enhancement framework. The performance of both feature extraction methods was evaluated with objective measurements and a subjective listening test to measure speech perception scores in terms of intelligibility and quality with 17 hearing-impaired listeners. Significant improvements in speech intelligibility and quality ratings were found for both feature extraction systems. However, the auditory-model based feature set showed superior performance compared to the comparison feature set indicating that auditory-model based processing could provide further improvements for supervised speech segregation systems and their potential applications in hearing instruments.**

Keywords—hearing aids; speech enhancement; deep neural networks; auditory models

I. INTRODUCTION

State-of-the-art hearing-aids successfully compensate for loss in audibility due to mild to moderate sensorineural hearing loss. At least in quiet acoustic conditions, users of such hearing-aids can obtain near-to-normal speech understanding. However, interfering noises still compromise the ability of hearing-aid users to follow conversations in more challenging acoustic conditions. Speech enhancement algorithms try to alleviate this problem by improving speech intelligibility through the attenuation of noise-dominated parts of the signal while retaining speech-dominated parts. Nevertheless, commonly used speech enhancement algorithms based on spectral subtraction or Wiener-filtering showed no or only minor speech intelligibility (SI) improvements in stationary and non-stationary background noises [1][2], most likely due to inaccurate assumptions about the statistical properties of the interfering noise. Specifically, background noises that contain speech-like characteristics (such as spectro-temporal modulation patterns, periodic components etc.) are likely to be misclassified as the target speech by these statistical-based speech enhancement algorithms.

More recently, supervised speech segregation has been proposed as a method for speech enhancement in hearing instruments [3][4]. This approach is based on the concept of the ideal binary mask (IBM) [5], which classifies the spectro-temporal representation of noisy speech into time-frequency (T-F) units either dominated by speech or by noise according to their instantaneous SNR and a pre-determined threshold. The IBM is employed as a training target for the supervised training process of a machine learning algorithm such as a deep neural network (DNN) [4] or Gaussian mixture model (GMM) [3] based classifier. The algorithm estimates the IBM based on a set of acoustic features being extracted from the noisy input signal in each time frame. Using this approach, [3] and [4] have shown large improvements in speech intelligibility for normal-hearing and hearing-impaired listeners.

However, [6] showed that the robustness of the segregation in "unseen" acoustic conditions is largely limited when the same noise recording was used for both training and testing of the classifier. Furthermore, the effectiveness of IBM-based speech segregation depends on an appropriate choice of the threshold-value in respect to the long-term SNR of the input sound. In practice, where the long-term SNR is unknown, this may lead to more estimation errors in binary masking algorithms compared to algorithms that use an ideal ratio mask (IRM) paradigm [7]. Recently, [8] and [9] addressed these aspects by employing the IRM as training target as well as evaluating the performance on novel segments of the background noise. Even in these more challenging testing conditions, significant improvements in speech intelligibility were found for hearing-impaired and normal-hearing listeners.

A comparison study [10] for different acoustic features found that linear gammatone features were the best performing single feature for a range of non-stationary background noises. The authors proposed a multi-resolution cochleagram feature (MRCG) based solely on the gammatone features and showed its' superior performance to a completely FFT-spectrum based feature set used in their previous studies. Thus, for supervised speech segregation systems, auditory inspired features based on the gammatone filterbank seem to be beneficial. However, the algorithm performance was only evaluated in one SNR condition (-5 dB) and no human listening tests were performed.

The auditory image model (AIM) [11] is a time-domain functional model of human auditory processing. It generates a series of two-dimensional representations of sounds referred to as "auditory images". For speech analysis, the "strobed" temporal integration mechanism of AIM generates a stabilized auditory image (SAI) that enhances the voiced speech parts without distorting the temporal fine-structure information. In addition, a scale-shift covariant version of SAI, called size-shape image (SSI) [12], is constructed via a normalisation

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process and results in a more stable pattern for different utterances of the same vowel spoken by speakers that differ in their vocal-tract lengths (VTL) [13]. Researchers at Google investigated the application of SAI in a machine-hearing application using a sparse-coding strategy [14] and suggested that AIM processing might improve robustness to noise.

In this study, we propose a novel auditory-inspired feature set comprised of features based on the linear gammatone filterbank (GT) [15] and the auditory image model (AIM). The motivation was to further improve the segregation performance obtained with GT-based features and their robustness to unseen conditions by incorporating the higher-level features of AIM processing. To our knowledge, this is the first study that applies AIM to the task of supervised speech segregation. As a benchmark, we compare the proposed feature set to the feature set used in [4] by combining both front-ends separately with a DNN-based speech segregation algorithm. The two DNN systems under test have been evaluated in terms of classification performance and recognition scores in a subjective listening test with hearing-impaired listeners. Similar to a more recent speech segregation study [8] we used the IRM as target function and "unseen" segments of noise for the testing dataset. Furthermore, the DNN framework was designed to generalize to a range of SNR conditions relevant for the target population.

II. Methods

A. Signal processing framework

The general signal processing framework (shown in Fig. 1) was based on a supervised speech segregation framework that applies a DNN to estimate the IRM for the enhancement of the noisy input signal. Firstly, the noisy input speech was analysed over 20 ms time windows with an overlap of 10 ms in a gammatone-based analysis and synthesis scheme [15]. For each time frame the GT envelopes were computed in 63 frequency channels ranging from 50 to 8000 Hz. The envelopes were then weighted with the estimated IRM gains from the DNN system and combined with the original noisy phase information to finally resynthesize the enhanced speech signal for presentation to the user. The two distinct sets of acoustic features were extracted from each frame and fed into the input layer of the DNN algorithm to produce an estimation of the IRM gain in each frequency channel.

B. Feature extraction

The comparison feature set (CO) was based on the one used in a recent study by [4] but following the procedures of [16] to compute features across all frequencies simultaneously in each time frame. The CO was exclusively based on features computed in the spectrum-domain using the fast Fourier transform. It was comprised of the 15-dimensional amplitude modulation spectrum (AMS) for each frequency channel (in total 63 x 15 dimensions), the 31-dimensional mel-frequency cepstral coefficients (MFCC) and the 12-dimensional RASTA-perceptual linear prediction coefficients (RASTA-PLP). Delta and delta-delta features of RASTA-PLP were added to incorporate temporal information of past frames, which resulted in a total dimension of 1012 per time frame for the CO feature set.

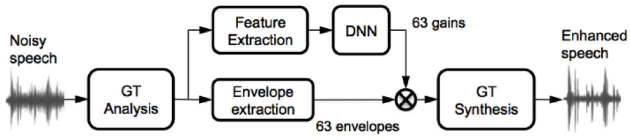

Fig. 1. Signal processing schematic of the DNN based speech segregation system using Gammatone (GT)-analysis and synthesis.

The proposed feature set (AU) combined linear gammatone features (GT-EN) and AIM features (SSI-DCT) to form an auditory modelling based feature set. The GT-EN features comprised the log-energies of the envelopes of the 63 output channels of the GT filterbank (with the same resolution as used in the analysis stage). The SSI-DCT features consisted of the lower-order discrete cosine transform (DCT) coefficients (2-22) of the 12 peak columns in the size-shape image (SSI) [12] constructed by the AIM [11]. The total dimension of the AU feature set amounts to 315, including 63 GT-EN features and 252 SSI-DCT features.

C. Neural network model

The DNN model consisted of a linear input-layer with the number of units given by the dimension of the feature set, two hidden layers with 100 and 50 units, and a linear output layer with 63 units determined by the number of frequency channels of the IRM target. Both hidden layers used a saturated linear transfer function (linear between 0 and 1, and saturated at values outside that range). The DNN was trained with the resilient backpropagation algorithm [17] in full-batch mode to minimize the mean squared error between the target values and the estimation. Weight decay regularisation was used to improve generalisation and increase robustness to the mismatch between training and testing data. The 80 training sentences (8 lists) were taken from the IEEE sentences [18] spoken by a male talker, and mixed with randomly selected segments of two types of 18s-long masking noises at 5 SNR levels (from -2 to 6 in steps of 2 dB). The masking noises consisted of a speech-shaped noise (SSN), with the same long-term spectrum as the target speech, and a multi-talker babble noise (BABBLE), artificially constructed by mixing random sentences of 4 male and 4 female talkers from the TIMIT corpus.

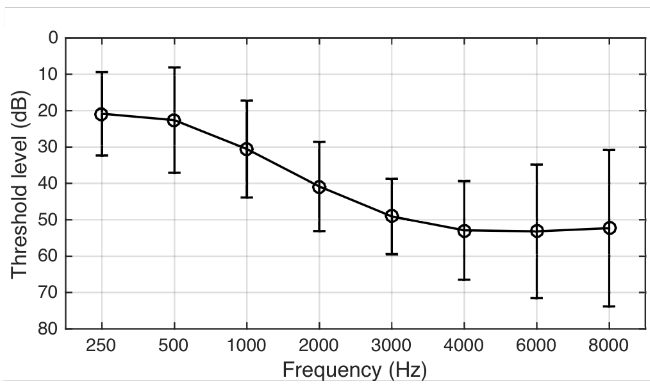

Fig. 2. Averages of the pure-tone audiometric thresholds of the tested ears for all participants (n=17). Error-bars represent standard deviations.

III. Evaluation

In order to evaluate the performance in mismatched conditions, 20 "unseen" sentences (2 lists) from the remaining lists of the IEEE corpus (male talker) were used for objective measurements of the classification accuracy. These lists constitute a part of the sentences that were used for the subjective listening test. The sentences were mixed at 0 and 4 dB SNR with randomly chosen segments of 8s-long noise recordings of SSN and BABBLE (original noise recordings were split into two non-overlapping parts: 16s long for training and 8s long for testing).

A. Objective evaluation: classification accuracy

We compared the estimation accuracy of the two DNN systems trained with CO features and AU features (referred to as DNN-CO and DNN-AU, respectively), by measuring the HIT-FA metric proposed by [3]. HIT-FA scores were obtained by subtracting the percentage of type-I classification errors (false alarms, FA) from the percentage of correctly classified speech-dominant T-F units (HITs). The HIT-FA metric has been shown to correlate with speech intelligibility scores and has been used in many speech segregation studies [4][8]. In order to compute HIT-FA scores, we converted the ratio masks (estimated and ideal) to binary masks by applying a local SNR criterion of -5 dB. HIT-FA scores were computed over the 20 testing sentences for each condition, and are listed in Table 1.

B. Subjective evaluation: listening experiment

Seventeen native-speaking hearing-impaired listeners (10 male, 7 female with an average age of 62.4 years) with mild-to-moderate hearing loss took part in the listening experiment. Participants were recruited through poster advertisement at the University of Southampton and the local community. All of them were regular users of hearing aids. During testing, participants did not wear their hearing aids and stimuli were presented to the better ear only. For each participant, compensation of hearing thresholds was performed according to the NAL-R procedure [19]. The averaged audiometric thresholds for the tested ears are shown in Fig. 2. The stimuli were generated with MATLAB using a laptop (Dell Latitude E7440) connected to a digital soundcard (RME Babyface) and presented via circumaural headphones (Sennheiser HD380pro) in a quiet room. The equipment was calibrated with clean speech to a presentation level of 65 dB SPL using a sound level meter (Brüel&Kjaer 2260) and artificial ear simulation (Brüel&Kjaer 4153). The study was approved by the local ethics committee.

Subjects were presented with 2 lists for each condition using randomised and latin square balanced orders [3 processing strategies (UN, DNN-CO, DNN-AU) x 2 SNRs (0, 4 dB) x 2 noises (SSN, BABBLE)]. A short training session was performed prior to the proper experiment using 1 list at 10 dB SNR to acclimatize to the testing procedure. Participants were asked to repeat the sentence they heard and the experimenter used a graphical user interface to select the correctly repeated keywords. Additionally, after a full list was presented, the participants were asked to rate the overall sound quality on a Likert scale with 7 steps (with labels at 1 - bad, 4 - fair and 7 - excellent). Each step of the scale was further subdivided into 10 substeps to allow for finer resolution.

TABLE I. Classification Accuracy results

% HIT-FA (FA)	SSN		BABBLE	
	0 dB	4 dB	0 dB	4 dB
DNN-CO	72 (8)	75 (7)	64 (18)	65 (17)
DNN-AU	76 (7)	79 (7)	67 (18)	67 (18)

IV. Results

A. Classification accuracy

HIT-FA scores (Table 1) indicated an advantage of DNN-AU over DNN-CO in terms of classification accuracy in all testing conditions. In the SSN condition, the feature set DNN-AU provided a benefit of 4% in HIT-FA scores in both 0 and 4 dB SNR. For the BABBLE noise condition, this advantage was reduced to 3% and 2% at 0 and 4 dB SNR, respectively.

B. Speech intelligibility scores

The percentage correct keyword scores are shown in Fig. 3. Statistical analysis with repeated measures two-way analysis of variance (ANOVA) indicated significant effects of processing condition in SSN [$F(16,1) = 126.88$, $p < 0.001$] and BABBLE [$F(16,1) = 17.10$, $p < 0.001$]. Bonferroni-corrected post-hoc comparisons showed a significant improvement of the DNN-AU algorithm over UN in SSN at 0 dB [$F(16,1) = 17.20$, $p = 0.003$] and in BABBLE at 0 dB [$F(16,1) = 114.32$, $p < 0.001$] and 4 dB SNR [$F(16,1) = 18.64$, $p = 0.0021$]. The DNN-CO algorithm showed a significant improvement in the BABBLE condition at 0 dB [$F(16,1) = 47.56$, $p < 0.001$] and 4 dB SNR [$F(16,1) = 11.95$, $p = 0.013$].

C. Speech quality ratings

The subjective speech quality ratings of the three processing conditions (UN, DNN-CO, DNN-AU) are shown in Fig. 4. A non-parametric Friedman's ANOVA indicated a significant effect of processing condition for SSN at +4 dB and BABBLE at 0 and +4 dB SNR. Bonferroni-corrected post-hoc

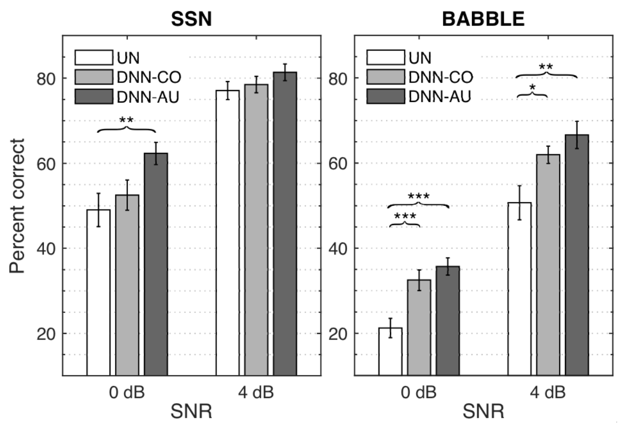

Fig. 3. Mean speech intelligibility scores of all 17 HI participants for unprocessed noisy speech (UN), the comparison feature set based DNN algorithm (DNN-CO) and the proposed auditory model based DNN algorithm (DNN-AU) for SSN and BABBLE noise. Error bars represent the standard error of the mean; (*)p≤0.05, (**)p≤0.01, (***)p≤0.001.

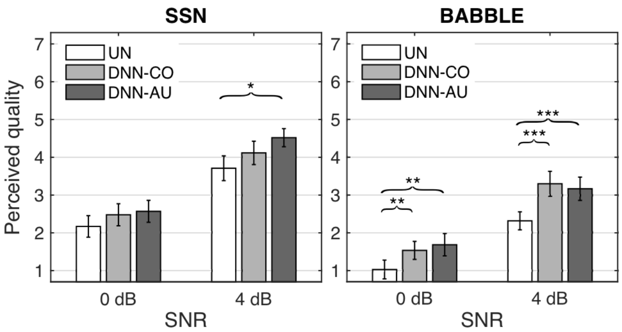

Fig. 4. Mean speech quality ratings of all 17 HI participants for unprocessed noisy speech (UN), the comparison feature set based DNN algorithm (DNN-CO) and the proposed auditory model based DNN algorithm (DNN-AU) for SSN and BABBLE noise. Error bars represent the standard error of the mean; (*)$p \leq 0.05$, (**)$p \leq 0.01$, (***)$p \leq 0.001$.

comparisons showed a significant improvement over the UN condition for DNN-AU in SSN at 4 dB SNR [$F(16,1) = 11.54$, $p = 0.015$] and in BABBLE at 0 dB [$F(16,1) = 15.07$, $p = 0.0053$] and 4 dB SNR [$F(16,1) = 24.07$, $p < 0.001$]. For DNN-CO there was a significant improvement over UN in quality ratings for BABBLE at 0 dB [$F(16,1) = 19.98$, $p = 0.0015$] and 4 dB SNR [$F(16,1) = 33.38$, $p < 0.001$].

V. Discussion and Conclusion

In this study we present a novel auditory-model based feature set with application to speech enhancement that builds on the framework of recently proposed DNN-based speech segregation systems [3][4][8]. The novel feature set combines linear GT filter bank features with AIM based features and shows superior performance compared to the comparison feature set in terms of HIT-FA rate and speech perception scores measured with a subjective listening test with hearing-impaired listeners. We further extend previous studies by employing the IRM target function and a range of SNR conditions for the training of the DNN to build a system that works independently from an SNR-threshold over the most relevant range of SNRs for the target users [2]. Furthermore, we measured subjective quality ratings in addition to intelligibility scores for all processing conditions to investigate if ratio-masking based speech enhancement improves the perceived quality for hearing-impaired listeners compared to unprocessed stimuli. As suggested by [6] and recently implemented by [8] we evaluate the system under test in novel segments of the noise background that was learned by the algorithm.

Both DNN systems achieved high HIT-FA scores (72-79%) with low FA rates (7-8%) in the SSN condition. Even though DNN-AU constantly obtained 4% higher HIT-FA scores, we did not expect to find such large difference in intelligibility scores at 0 dB SNR between the two DNN systems in the listening test. Only the DNN-AU algorithm gave a significant improvement by 13% at 0 dB SNR. In this case, the chosen SNR threshold for conversion into a binary classification metric might not be sensitive enough at low SNR levels (0 dB), when ratio masks are applied to the noisy input signal. Furthermore, speech distortions due to underestimation effects are ignored by the HIT-FA metric and might degrade speech understanding (e.g. at the easier condition at 4 dB SNR). For the BABBLE noise condition, where the advantage in HIT-FA scores of the DNN-AU system was slightly reduced to 2-3%, reliable and highly significant improvements have been found for both DNN algorithms (e.g. 14-16% for DNN-AU over UN).

Comparing to previous supervised speech segregation studies, especially to [8], our algorithm was able to reproduce the significant improvements in speech intelligibility for hearing-impaired listeners even though our system achieved smaller improvements in intelligibility (13-16% compared to 18-44%). There are several potential reasons for this difference in performance: Firstly, our DNN-system uses a much smaller architecture (2 hidden layers with 100 and 50 units) with significantly less training data (several minutes opposed to hours in [8]). We chose this DNN-architecture based on a previous study evaluating a DNN-based speech segregation system for NH participants listening to CI simulations (noise-vocoded stimuli) [9] where we found the given choice of hyper-parameters to constitute a good compromise in terms of algorithm complexity and estimation accuracy. Secondly, our system estimates the IRM using only features computed from the current time frame (i.e. no future frames) thus yielding a real-time feasible algorithm. Thirdly, we train only one DNN per background noise to generalize over a range of SNR conditions that might be a challenging task for such a small architecture. Nevertheless, our results are in line with the findings of [8] and support the promising application of DNN-based speech segregation for hearing-impaired listeners.

In addition to measuring speech understanding we investigated whether HI listeners preferred the speech quality of the processed speech compared to the unprocessed noisy speech. We found consistent improvements in perceived quality in SSN for both DNN-systems, again with an advantage for the DNN-AU algorithm which achieved a significant improvement at 4 dB SNR by about 0.81 rating points. In BABBLE, both systems achieved significant improvements in all conditions (from 0.5 up to 1 rating point) for the perceived speech quality, whereas DNN-AU reached the best quality in 0 dB and DNN-CO in 4 dB SNR. This finding further supports the potential application of DNN-based speech segregation as speech enhancement technique for hearing-impaired listeners, because for improved speech perception both aspects (intelligibility and perceived quality) have to be improved in parallel. This indicates a step forward in comparison with conventional speech enhancement techniques, which mostly improve the listening effort and perceived quality of the noisy speech but struggle to show significant improvements in intelligibility.

Overall, the DNN-AU algorithm showed better performance in comparison with the DNN-CO algorithm which supports the hypothesis that processing techniques inspired by the human auditory system are beneficial for technical systems that try to improve human perception of speech sounds. However, this conclusion is limited to the current setup and testing approach we used.

One of the main challenges for supervised speech separation is its ability to generalize to acoustic environments different from the ones seen during training. In this study we evaluated the system performance according to [6] on novel segments of the background noise and showed that still significant improvements are obtained even with a much smaller DNN system than previous studies used. In respect to applications in real-world hearing devices this might be beneficial due to restricted computational and memory resources. Still, further aspects of generalization performance need to be addressed in future studies that evaluate unseen multi-speaker and multi-noise scenarios where further optimizations for the training process are likely to be required.

In conclusion, we presented a DNN-based speech segregation algorithm in conjunction with two different feature sets and evaluated its performance objectively and in a subjective listening test with hearing-impaired listeners. Our findings are in line with previous studies and indicate further evidence that auditory-model based features are able to improve the segregation process. We further add to previous studies that reported benefits for speech intelligibility by showing that ratio mask based processing improves the perceived quality of the noisy speech for HI listeners also in the non-ideal case with an estimation algorithm. Significant improvements in both perceptual aspects of speech, perceived quality and intelligibility, achieved by a more real-time feasible algorithm, provide a step forward to real-world applications of supervised speech segregation systems for hearing-impaired listeners.

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