Towards accurate simulations of individual speech recognition benefits with real hearing aids with FADE

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Abstract

Developing and selecting hearing aids is a time consuming process which could be simplified by using objective models. The framework for auditory discrimination experiments (FADE) accurately simulated the benefit of hearing aid algorithms. One simulation with FADE requires several hours of (un)processed signals, which is obstructive when the signals have to be recorded. We propose and evaluate a real-time optimized and data-reduced FADE version (“ROR-FADE”) which enables simulations of speech recognition thresholds (SRTs) with about 30 minutes of recorded and potentially processed signals of the (German) matrix sentence test. SRTs were simulated for different noise maskers, degrees of hearing loss, and with simulated hearing aids. At last, speech recognition with three pairs of real hearing aids was simulated. The differences between ROR-FADE and FADE were small for stationary maskers (1 dB), but larger with strongly fluctuating maskers (5 dB). Hearing impairment and hearing aid algorithms seemed to reduced the differences. Hearing aid benefits were found in silence (≥8 dB), in stationary and fluctuating maskers in co-located (stat. 2 dB; fluct. 6 dB), and spatially separated speech and noise signals (stat. ≥8 dB; fluct. 8 dB). The simulations were plausible in comparison to data from literature, but a comparison with empirical data is still open. ROR-FADE simulates SRTs in about 30 minutes in any setup that uses matrix sentences. Therefore, it facilitates objective SRT simulations with real devices with unknown signal processing in real environments. Consequently, ROR-FADE could be used for model-based hearing aid fitting or for the development of hearing aids.

Keywords: Speech Intelligibility Prediction, FADE, Modeling, Hearing Aids, Aided Patient Performance Prediction

1 Introduction

Hearing impairment imposes a barrier within the daily life of many people as it impedes conversations and the perception of (warning) sounds. Hearing aids are a solution to counteract hearing impairment and to improve speech recognition. However, finding the best hearing aid and fitting for an individual is difficult and time-consuming (Boymans and Dreschler, 2012; Völker et al., 2018). The development of hearing aids and algorithms is also time consuming and prone to errors when predicting their possible benefits for speech recognition with models, such as, e.g., the SII (ANSI, 1997) or iSNR (Greenberg et al., 1993) (e.g., Baumgärtel et al. (2015) and Völker et al. (2015), or see Falk et al. (2015) and Kollmeier and Kiessling (2018) for an overview). These and more recent models that predict hearing device performance (e.g., HASPI Kates and Arehart 2014, HASQI Kates and Arehart 2010, STOI Taal et al. 2010) have three disadvantages: First, they predict index values whose perceptual meaning is intransparent. Second, most published models often perform only well for specific tasks (e.g., only with stationary maskers), such that the task defines which model should be used (Falk et al., 2015). Third, such models are intrusive and require some form of separable speech and noise signals. This poses another obstacle when signal and noise need to be separated after processing which requires assumptions about the non-linear system (see Schädler et al., 2018, for an overview).

The aim of this paper is to provide and evaluate a model for the accurate simulation of hearing aid benefits that can be used with real devices. The process to develop, evaluate, and optimize hearing aids and their algorithms can profit from objective models that accurately predict benefits in a fast and convenient way. The potential advantage of such simulations is even higher if models are used that predict the benefit of real devices. Real devices typically show deviations from the idealized behavior of the respective underlying hearing aid algorithm. That is, real signals are recorded and environment-specific modifications of the underlying combination of signal processing algorithms are performed. These complex interactions between the acoustic environment, the acoustic paths, and the respective algorithm may even not be accessible when modeling hearing aids. Therefore, several pitfalls are avoided by using real hearing devices. Yet, at the time of writing, no model allows to directly simulate benefits of real hearing aids, at last in a practicable time frame.

In addition, to be instrumental in individual recommendations, the individual benefit of hearing aids has to be
predicted accurately which imposes a difficult task: Only a limited success in predicting hearing aid benefits was achieved on the individual prediction task for hearing aid algorithms (e.g., Baumgärtel et al., 2015; Fulk et al., 2015). Further, the currently available estimates of average improvement prediction by index values (e.g., Kates et al., 2018) are not yet validated for the individual aided performance prediction with real hearing devices. Thus, the actual hearing aid benefit remains unknown.

Schädler et al. (2016b) proposed the framework for auditory discrimination experiments (FADE) which uses automatic speech recognition (ASR) to simulate human speech recognition to overcome limitations of traditional models (available online, see FADE, 2016). The approach does not require separated speech and noise signals and it was shown to accurately predict SRTs and algorithm benefits of listeners with normal and impaired hearing in a number of stationary and nonstationary noise and aided listening conditions (Schädler et al., 2018; Schädler et al., 2020, 2016b). The downside of the training procedure is that FADE requires several hours of mixed speech and noise signals. This makes it difficult to use FADE with any algorithm or device that can only process signals in real time. For example, simulation performed by Schädler et al. (2018) or Schädler et al. (2020) would allow for two to three simulations per day since they required about nine hours of mixed signals to simulate one speech recognition threshold (SRT), i.e., the signal-to-noise ratio (SNR) with a 50% recognition rate. However, many of the recordings are discarded at some stage of the SRT estimation process while only signals mixed at one training SNR and two test SNRs, i.e., 50 minutes of signals, currently provide the simulation outcome.

An objective, non-intrusive, reference-free, and plausible simulation method for aided speech recognition performance is desirable which operates on an amount of speech data which is as small as possible. Yet, non of the aforementioned models fulfills all of these criteria. Therefore, we propose a real-time-optimized and data-reduced version of FADE (denoted as ROR-FADE) and test it for the accurate simulation of aided and unaided speech recognition performance. Such an approach might reduce the time required to find hearing aids for individuals and accelerate the development of hearing aids in an objective and evidence-driven way.

The accuracy of the ROR-FADE approach can be shown by comparing it with simulations of the original FADE model, as well as with data from current literature. For that purpose, measured SRT data and FADE simulations with normal hearing (Schädler et al., 2016a,b), hearing impairment (Hülsmeyer et al., 2016; Wardenga et al., 2015), and hearing impairment together with hearing aid algorithms (Schädler et al., 2020) were used. However, no appropriate empirical data is available for comparison for simulations with real hearing aids, simply because the hearing aids’ signal processing approaches are unknown. Yet, when the plausibility of the model approach can be demonstrated, it—in theory—facilitates model-based hearing aid fitting or its application as an assistance during the hearing aid development process.

Here, aided and unaided speech recognition performance is simulated with the matrix sentence test, which can be used to reliably measure SRTs (test-retest reliability of 1 dB, Kollmeier et al., 2015, available in more than 20 languages). It provides syntactical fixed and semantically unpredictable sentences and is typically used in clinical practice to determine the individual listening performance and to determine which hearing aid provides the highest individual benefit, i.e., an improvement in SRT. The sentences of matrix sentence tests are composed of a name, verb, number, adjective and an object, e.g., “Peter has five wet chairs”, where each word class (e.g., name) has ten alternatives (50 words in total). Matrix tests use simple grammar structures in combination with limited semantic and linguistic complexity, such that little cognitive capabilities are required to perform these tests. Thus, mainly the ability to recognize words is examined with this test. Other speech recognition tests exist that require more cognitive capabilities to perform due to their linguistic complexity (e.g., Kollmeier and Wesselkamp, 1997; Nilsson et al., 1994), or do not use sentences (e.g., Hoth, 2016). Matrix tests have been successfully used in many studies for assessing the benefit for a large range of hearing devices (e.g., hearing aids Neher et al. 2017, assistive listening devices Ihler et al. 2016; Rennies et al. 2017 or cochlea implants Williges et al. 2015). Further, matrix sentence tests are an ideal test for machine-learning-based objective prediction methods (Schädler et al., 2016b). That is, their structure and vocabulary size simplify the ASR system’s language and acoustic model. Therefore, simulated SRTs of the (German) matrix sentence test are used as the prime measure to quantify speech recognition performance throughout this study. Note that FADE only takes into account spectro-temporal modulations and hearing loss to simulate SRTs and does not explicitly take into account the overall presentation level (closely related to loudness), listening effort, or other measures of hearing aid performance.

The research hypotheses to be tested in this paper are:

- Is ROR-FADE suitable to accurately predict aided and unaided speech recognition performance in a reasonable time span?
- Does ROR-FADE predict plausible benefits for real hearing aids?

2 Methods

2.1 Model approach

2.1.1 Framework for Auditory Discrimination Experiments

FADE is a model that simulates the outcome of auditory discrimination experiments, i.e., of psychoacoustic or of speech recognition experiments. Its modeling scheme is depicted in Figure 1. First, speech and noise signals are mixed at different SNRs for training and testing the hidden Markov model with Gaussian mixture model (GMM-HMM) speech recognizers. FADE uses one recognition system per training SNR to simulate the outcome of speech recognition
experiments based on the (German) matrix sentence test. About 40 minutes of training signals (i.e., 960 matrix sentences) and about five minutes of test signals (i.e., 120 sentences) at each SNR are required with the standard parameters of FADE. Thus, a standard simulation with assumed normal hearing and eleven SNRs requires about nine hours of train and test signals. Next, spectro-temporal representations of the signals, i.e., logarithmically scaled Mel spectrograms, are calculated for each signal. Then, features are extracted from them and used for training and testing the speech recognition systems of FADE. At last, the recognition rate is calculated for each training and test SNR and it is depicted in a recognition map (see Fig. 1). There, the recognition performance is plotted as a function of the SNR used for training different speech recognition systems against the test SNRs. The SRT is then estimated as the lowest interpolated test SNR which yields a 50 %-correct rate.

Binaural hearing is taken into account by calculating and concatenating separate features when two signal channels are present, i.e., one for the left and another for the right ear. With this approach, the recognition systems automatically use the optimal statistics to recognize words, however without taking into account any binaural interactions (comparable with better ear listening Hauth and Brand, 2018). Signal energy below the absolute threshold was removed from the logarithmically scaled Mel spectrogram when hearing loss was used (Hülsmeier et al., 2020; Kollmeier et al., 2016). Therefore, the absolute threshold was converted to dB SPL using ISO:226 (2003) and a freefield to eardrum correction (Shaw and Vaillancourt, 1985). The correct application of the absolute threshold can be examined by simulating a psychoacoustic tone detection experiment or by iteratively adjusting the tone level until its spectral representation vanishes (Hülsmeier et al., 2020).

For more details on FADE and its implementations, please refer to Schäddler et al. (2016b) and Schäddler et al. (2018).

2.1.2 Modified FADE (ROR-FADE)

The standard FADE model is comparable to a brute-force method that uses a broad range of SNRs and a large amount of signals to estimate and assess one single SRT. To reduce the required amount of signals for one simulation, the standard FADE version was modified based on assumptions about the model. These modifications are i) model initialization, ii) SRT approximation, iii) SRT simulation, and iv) model evaluation.

i) Initialization A rough initial estimate of the SRT is made based on the average hearing loss for frequencies below 1 kHz and the noise level. This assumptions was found to be representative for the German matrix sentence test and various degrees of hearing loss (Hülsmeier et al., 2016). The estimated SRT is the maximum of either the average hearing loss for frequencies below 1 kHz in dB SPL, the SRT dependent on the noise level in dB SPL (about -8 dB SNR), or the SRT in silence. The motivation for this step is to yield a SNR close to a 50 % recognition rate for different degrees of hearing loss and noise levels, such that less signals are required in the following to find the lowest SRT. The hard coded estimation is motivated by SRTs in silence and in stationary, unmodulated noise, and their relation to the average hearing loss (Hülsmeier et al., 2016; Kollmeier et al., 2016; Plomp, 1978; Wardenga et al., 2015).

ii) SRT approximation A pre-simulation is conducted where the SRT is approximately starting from the rough initial SRT estimate with matched-SNR training, i.e., when train and test SNRs are equal (leading to the SRT estimate marked with a (blue) cross in
panel a of Fig. 2). For this purpose, the recognition performance for a single word class of the matrix sentence test (here: names) is determined to reduce the training data by a factor of five while adjusting the SNR. The number of training signals is initially reduced by a factor of 8 from 960 to 120 mixtures. In total, this reduces the amount of training signals form 40 minutes to 75 s per SNR. The number of test signals is initially reduced by a factor of 4.8 from 120 to 25 names, i.e., to 15 s. Both train and test signals are used three times to obtain sufficient signals for training and to yield a resolution of 1 % (100 words) for the recognition process. The estimated SRT is then either interpolated between two SNRs if two rates between 25 % and 75 %-correct are found, or it is set to the SNR which yields a correct rate within (50±15) %. In total, this step requires about 90 s of signals for a simulation with one SNR and converges after 3.0±1.6 iterations (i.e., 4.3±2.3 min).

![Figure 2: Recognition map during adaptive search for the predicted SRT with ROR-FADE.](image)

### iii) SRT simulation
An adaptive search for the lowest SRT is started (panels b to c in Fig. 2) which initially uses 120 train and 20 test sentences and thereby reduces the required signals per SNR from 45 to six minutes (training: 5 min, test: 1 min, factor 7.5): Two train and four test SNRs (10 + 4 min) are selected in dependence on the pre-simulation (panel a), where the training SNRs are 3 and 9 dB greater and the test SNRs are -9, -6, -3, and 0 dB lower than the estimated SRT (panel b). This SNR area is selected based on the typical pattern shown in all recognition maps: The lowest SNR with a 50 % recognition rate, i.e., the desired outcome of the simulation, has a greater or equal training SNR and a lower test SNR than found for the SNR on the diagonal of the recognition map that yields a 50 % recognition rate (e.g., as depicted in the block “Recognition map” in Fig. 1). Subsequently, the SNR area is adapted until a minimum SRT is found:

- Increase the test SNRs by 3 dB if all recognition rates are lower than the target rate, or
- Decrease the test SNRs by 3 dB if all recognition rates are greater than the target rate, and/or
- Increase the training SNRs by 6 dB if the recognition rate is found for the highest examined training SNR, or
- Decrease the training SNRs by 6 dB if the recognition rate is found for the lowest examined training SNR (e.g., panel c), and/or
- Decrease the test SNRs by 3 dB if less than two test SNRs are below the SRT (e.g., panel b), or
- Otherwise stop the simulation (e.g., panel d).

During these steps, the signals recorded at different SNRs are reused, i.e., each new test SNR is tested against all available and learned models for the training SNRs, and vice versa. Thereby, the signals are recorded while the other simulation steps (feature extraction, training and testing of the speech recognizers, and evaluation) run simultaneously whenever it is feasible, such that signals are recorded while running the remainder of the simulation process.

### iv) Evaluation
The amount of train sentences to determine the SRT is artificially doubled by applying multi-condition training which generally improves the recognition performance (Hirsch and Pearce, 2000). Therefore, signals recorded at two SNRs, e.g., at -3 and +3 dB SNR, are used for training one combined speech recognizer. Note, that this does not require to make any further recordings, but allows for more accurate predictions of conditions that normally require more data, e.g., simulations with fluctuating maskers. The simulated SRT is defined as the lowest SNR with a 50 %-correct recognition rate found with multicondition training.

The original parameter set of FADE was tuned on speech recognition and tone detection experiments. Schädler et al. (2016b) found that 120 training sentences were sufficient to simulate speech recognition in stationary noise but recommended using 960 as this resulted in lower tone detection thresholds. Thus, SRT’s simulated with ROR-FADE and fewer signals can be expected to be similar to the SRT’s simulated with FADE for simulations conducted with maskers that have little variance, or when the dynamic range of the signals is reduced to elevated absolute thresholds. The differences between FADE and ROR-FADE likely increase with fluctuating maskers, since using fewer train sentences results in a poorer representation of maskers with large variance by FADE’s GMMs. It is also less likely to find the best training SNR with ROR-FADE since the training
SNRs are sampled in 6 dB steps (3 dB steps with FADE). Further, it can be expected that the amount of training signals affects the total amount of signals required for one simulations more than the amount of test signals.

2.2 Experiment 1: Benchmarks

In order to select suitable conditions to compare the simulation results of FADE and ROR-FADE and to estimate the minimum amount of training and test data to be used by ROR-FADE, the following requirements had to be fulfilled: First, the number of train and test signals should be meaningful for simulations with various maskers under the constraint that the simulations do not require much more than 30 minutes per SRT. Second, the baseline for simulations, i.e., SRT simulations of listeners with normal (and impaired) hearing without any hearing aid, should be accurate and yield similar outcomes with both FADE versions. I.e., those preliminary versions of ROR-FADE were excluded from further considerations that did not produce simulations with a sufficiently small prediction error due to a too much reduced dataset. Third, for the same reason, both FADE versions should predict similar aided hearing performance. Note, all of the benchmark simulations were conducted digitally, i.e., no signal was required to be recorded for the simulations.

2.2.1 Benchmark 1: Number of training and test signals

The effect on the SRT of the number of train sentences used with ROR-FADE was examined for 120 to 960 sentences. The number of test sentences was examined for 20, 40,..., and 120 sentences, which equals one to six lists used for measuring SRTs of human listeners. The prediction performance with a given number of sentences was examined with a normal-hearing configuration and a fluctuating masker at 65 dB SPL. Listeners with normal hearing typically reach SRTs of less than -19.0 dB SNR (Hochmuth et al., 2015; Wardenga et al. (2015) and Hülsmeyer et al. (nodate). The SRTs were measured monaurally using the stationary, test specific noise (tsn) at 65 dB SPL. The simulations were statistically examined with the root-mean-squared error (RMSE, Armstrong and Collopy, 1992), the bias (i.e., offset from the diagonal indicating a perfect correlation), and the coefficient of determination $R^2$ (i.e., the squared Pearson correlation coefficient).

2.2.2 Benchmark 2: Unaided hearing

FADE and ROR-FADE were compared with SRT simulations in different stationary (icra1f, icra1m, and test specific noise, taken from Schädler et al., 2016a,b), multitalker (babble, taken from Schädler et al., 2016a), and fluctuating maskers (icra4-250m, and icra5-250m, taken from Schädler et al., 2016a). These baseline conditions were extended with one additional masker (multitalker: cafeteria) and silence. Further, ROR-FADE was compared with two empirical SRTs for the stationary icra1m and the fluctuating icra5-250m masker (Hochmuth et al., 2015). The masker levels were set to 65 dB SPL. Each of the simulations was conducted 512-fold.

The effect of hearing loss on the simulations was examined with SRTs of 315 ears with hearing impairment from Wardenga et al. (2015) and Hülsmeier et al. (nodate). The SRTs were simulated digitally, i.e., no signal was required for the simulations. The number of test sentences was examined for 20, 40,..., and 120 sentences, which equals one to six lists used for measuring SRTs of human listeners. The prediction performance with a given number of sentences was examined with a normal-hearing configuration and a fluctuating masker at 65 dB SPL. The simulations were statistically examined with the root-mean-squared error (RMSE, Armstrong and Collopy, 1992), the bias (i.e., offset from the diagonal indicating a perfect correlation), and the coefficient of determination $R^2$ (i.e., the squared Pearson correlation coefficient).

2.2.3 Benchmark 3: Aided hearing

FADE and ROR-FADE were compared with aided SRT simulations of Schädler et al. (2020). The simulation accuracy was statistically examined with RMSE, bias, and the coefficient of determination $R^2$. Schädler et al. (2020) measured and simulated SRTs of 18 listeners with different degrees of hearing loss. They used the German matrix sentence test in silence and in stationary (icra1m) and fluctuating (icra5-250m) noise at 65 dB SPL. The signals were processed with different hearing aid algorithms via openMHA (Herzke et al., 2017) that included linear amplification, compression amplification, and compression amplification with a noise-suppressing beamformer.

2.3 Experiment 2: Hearing aid benefit

ROR-FADE was used to simulate SRTs with and without the provision of three real hearing aid pairs from three leading hearing aid manufacturers. Therefore, hearing aids were put on a dummy head which was placed inside an anechoic chamber (Fig. 3). Speech and noise signals were presented via loudspeakers with a fixed noise level of 65 dB SPL calibrated at the center position of the dummy head with an omnidirectional microphone. SRTs were simulated with ROR-FADE which steered the sound presentation and the recording. A comparison with standard FADE was not feasible in a reasonable time frame, i.e., each simulation with FADE would require more than 9 hours of signals (i.e., about one month of simulation time for all conditions).

The dummy head had two low noise microphones with a sensitivity lower than the absolute threshold of normal hearing listeners (Wille and Rasmussen, 2016), with the exception of frequencies between 2.5 and 5.0 kHz where it was about 2 dB above the normal-hearing threshold. The absolute hearing threshold on both ears was set to the
profile N3 described by Bisgaard et al. (2010), i.e., a moderate high-frequency hearing loss which can be assumed to impede daily communication when found in human listeners. The correct application of the absolute threshold was tested by recording pure tones and by analyzing the logarithmically scaled Mel spectrograms of the signals. This procedure is similar to standard pure tone audiometry, i.e., the level of pure tones were adjusted until the Mel spectra of the signals were not distinguishable from recordings without pure tones.

The three (behind-the-ear) hearing aid pairs were on an approximately similar technological level (Tab. 1), i.e., their peak levels, maximum amplification, frequency range, microphone noise, and number of adjustable channels was alike. Further, all devices had directional beamformers, noise suppression, and used double domes as ear-pieces. The implementation of the hearing aid processing was not specified for any of the devices. Therefore, the hearing aids can be thought of as black boxes that record, (non-linearly) process, and play sounds. A simulation with normal-hearing thresholds was conducted to indicate if the hearing aids can restore simulated normal-hearing speech recognition performance. Therefore, the normal-hearing condition can be considered as fourth “hearing aid”.

For each simulation, hearing aid pairs of one manufacturer and with the same fitting were placed on the dummy head. The insertion of the hearing aid ear-pieces was controlled with a broadband noise to check if the same frequency response was found for the left and right ear. The orientation of the dummy head, i.e., if the dummy head faced the front, was verified with an impulse played back from the loudspeaker in front of the dummy head and recording the time signal at both ears. Thus, the dummy head was considered as facing to the front if the impulse reached the dummy head’s ears at the same time.

An overview of the measurement conditions is listed in Table 2. The simulations were conducted in silence and in stationary (icra1m) and fluctuating (icra5-250m) maskers and with two spatial configurations, i.e., co-located speech and noise signals from the front (S0N0), and speech from the front and noise separated by 90° to the left (S0N90). The unaided SRT with hearing impairment was simulated eight-fold to provide a reference with low variance for determining hearing aid benefits. Otherwise, and due to a lack of simulation time, standard deviations of the simulations were taken from the second benchmark experiment. The standard deviation of the hearing aid benefits were calculated using Gaussian error propagation.

3 Results

3.1 Experiment 1: Benchmarks

3.1.1 Benchmark 1: Number of training and test signals

The differences between ROR-FADE and FADE for the fluctuating icra5-250m masker in dependence on the number of training and test signals are depicted in Figure 4. As expected, the ROR-FADE simulations generally showed 2 to 5 dB higher SRTs. The differences were mostly determined by the number of train sentences while changing the number of test sentences had a smaller effect on them. The SRT differences were about 5 dB when 120 training sentences were used and about 3 dB with 240 training sentences. The differences remained between 3 and 2 dB when more training (or test) sentences were used. Interestingly, a difference of about 1.5 dB was found even when the standard number of train and test sentence (i.e., 120 test and 960 train sentences) was used (discussed later).

The time required for one simulation increased with the number of sentences, which was more affected by the amount of training sentences than by the amount of test sentences. To assess the tradeoff between simulation accuracy and time for the simulation, the Accuracy Speed Tradeoff (AST, Eq. 1) was computed which is displayed in the lowest panel of Figure 4. The lowest AST was found for 240 training and 20 test sentences. Further low ASTs were found when 120 or 240 training sentences were used in combination with 20 or 40 test sentences. Even though employing 120 training sentences appears promising due to the least time consumption and a reasonable low AST, this condition provided the highest difference in SRT which may limit its usage for practical simulations. However, these differences are expected to be much smaller in continuous noise than in the fluctuating noise employed here. Therefore, further simulations were conducted with 120 and 240 training and 20 test sentences per SNR.

3.1.2 Benchmark 2: Unaided hearing

The difference in SRT between ROR-FADE, FADE and two empirical measurements are depicted as boxplots in Figure 5. In general, SRTs simulated with ROR-FADE were higher (worse) than with FADE. With 120 training sentence, median differences of less than 2 dB were found when no masker or stationary maskers were used. The median differences were about 3 dB with multitalker maskers and about 5 dB, with fluctuating maskers. However, the median differences were about 1.5 dB when the Bisgaard profile N3 was used together with the fluctuating icra5-
Figure 6 depicts the differences in SRT between ROR-FADE and FADE for 315 hearing-impaired ears simulated in the stationary test-specific masker (tsn) and the empirical measurements. The simulations of both FADE versions correlate with an R² of 0.99. However, the bias and RMSE indicate that hearing impairment might introduce an additional offset of about 1 dB from standard FADE: Both quantities exceeded the median offsets depicted in Fig. 5 by about 1 dB. The measured SRTs were better predicted with 120 training sentences than with 240 training sentences. Yet, both version of ROR-FADE showed high correlations with the empirical data as well as low bias and RMSE values.

### 3.1.3 Benchmark 3: Aided hearing

The data of Schädler et al. (2020) were re-simulated with ROR-FADE with 120 and 240 train and 20 test sentences. The differences in SRT between ROR-FADE, FADE and the empirical measurements are depicted in Figure 7. The simulations showed perfect correlations between ROR-FADE and FADE (R²=1.0), as well as low bias and RMSE values (≤2.2 dB) for all hearing aid algorithms. Similar outcomes were found in comparison to the measured SRTs, i.e., SRTs predicted with both ROR-FADE versions showed high correlations (R² ≥0.9), as well as low bias (≥-2.5 dB) and RMSE values (≤4.6 dB) for all hearing aid algorithms. On average, ROR-FADE simulated higher SRTs than FADE, while it simulated SRTs lower than measured ones. In comparison to FADE, neither hearing aid algorithms nor hearing impairment seemed to introduce further variance to the ROR-FADE simulations for this data set, while the empirical SRTs were accurately predicted.
3.2 Experiment 2: Hearing aid benefit

The SRTs and benefits simulated with and without the three hearing aid pairs are depicted in Figure 8. Hearing-aid benefits were found for all devices and conditions.

3.2.1 Unaided listening

Generally, the unaided SRTs for the co-located $S_0N_0$ condition were at expected thresholds and matched previous simulations (Hülsmeier et al., 2020) when taking the offset between ROR-FADE and FADE into account (e.g., Fig. 5). The spatial separation of speech and masker ($S_0N_0$) led to lower SRTs when normal hearing was assumed, but seemed not to affect the SRTs simulated with hearing impairment. As expected, the largest difference between normal and impaired hearing was found for the simulation in silence (>30 dB) followed by the fluctuating masker (15 dB) and the stationary masker (2 dB). These gaps increased when speech and noise were spatially separated. The release from masking due to masker fluctuations (FRM), i.e., the difference between the stationary and the fluctuating masker, was about 9 dB with normal hearing in the co-located, and about 5 dB in the spatially separated condition. This trend reversed with hearing impairment, where the benefit was about -3 dB in both conditions. Further, no spatial release from masking (SRM), i.e., the difference between SRTs in the co-located and the spatially separated condition, was found with the hearing-impaired configuration. An SRM of about 5 dB was found with the simulated normal-hearing configuration and a stationary masker, but the SRM was only about 2 dB with the fluctuating masker.

3.2.2 Aided listening

The benefits with the stationary masker in the co-located $S_0N_0$ condition were on par with the required benefit to restore simulated normal-hearing performance (left lower panels of Fig. 8). A benefit between 5 and 7 dB was simulated with the fluctuating masker, albeit a gap of about 7 dB remained between the aided and the required benefit to restore simulated normal-hearing performance. In silence, the hearing aid benefit with the manufacturer fitting was about 14 dB for all devices, and with the NAL-NL2 fitting about 9 dB for devices A and C and about 17 dB with device B. However, a gap of about more than 20 dB towards the required benefit to restore simulated normal-hearing performance remained. Apart from the simulations in silence only minor differences ($\leq 2$ dB) between the fitting methods and devices were found for the co-located condition.

The simulated benefit in the spatially separated $S_0N_0$ condition exceeded the required benefit to restore simulated normal-hearing performance with the stationary masker by about 2 to 3 dB for devices A and C, and by 9 dB for device B. The gap towards the required benefit to restore simulated normal hearing performance was about 7 dB with the fluctuating masker, i.e., comparable to the gap simulated in the co-located condition.

4 Discussion

4.1 Model comparison

The real-time-optimized and data-reduced ROR-FADE facilitates to use real devices to process signals when simulating speech recognition thresholds without the need of empirical reference SRTs. Therefore, the real acoustic properties and pathways of the hearing aids and the receiving dummy head can be used for the simulations. Nonetheless,
FADE is not a human recognizing speech but a machine that uses an artificial auditory system with basic binaural features. Therefore, such simulations should always be interpreted with care. To simulate on SRT ROR-FADE uses less than one hour of (un)processed speech signals at the cost of a lower simulation accuracy in comparison to standard FADE.

The amount of (un)processed signals required by ROR-FADE seems still high compared to established prediction models that typically use less than a minute of signals. However, such models are often limited to specific speech recognition problems (ANSI, 1997; Beutelmann et al., 2010; Fontan et al., 2020; Kates and Arehart, 2014; Taal et al., 2020), which restricts their general applicability. In order to predict aided speech recognition performance in realistic environments, models need to take into account hearing impairment, binaural hearing, realistic maskers, reverberation, and processed signals (with real devices). For example, the SII (ANSI, 1997) takes into account hearing impairment but neither binaural hearing nor processed signals. BSIM (Beutelmann et al., 2010) takes into account binaural hearing but not processed signals. HASPI (Kates and Arehart, 2014) was designed to simulate aided speech recognition performance, but without taking into account fluctuating maskers (see Schädler et al., 2018, Tab. 1 for a comparative list).

Most of these model characteristics are covered with FADE and ROR-FADE for the simulation of real hearing aids. However, the current version of FADE (and ROR-FADE) neglects several binaural effects, e.g., temporal fine structure (Moore et al., 2012; Neher et al., 2012) or the medial olivocochlear reflex (Lopez-Poveda et al., 2016). Albeit it uses an automatic form of better ear listening (gray) to indicate the benefit required to restore normal-hearing performance (e.g., 37 dB in silence). The panels on the left show data for co-located speech and maskers from the front (SN0), while the right panels show data for speech separated from the maskers by 90° to the left (SN90). Error bars indicate the standard deviation (with Gaussian error propagation for hearing aid benefits) estimated from standard deviations from the second benchmark (Fig. 5).

4.2 Experiment 1: Benchmarks

The first benchmark showed, that ROR-FADE can predict SRTs with less than 30 minutes of (un)processed speech signals at the cost of the simulation accuracy. Still, ROR-FADE even simulated 1.5 dB higher (i.e. worse) SRTs than FADE when using 960 sentences for training and 120 for testing the speech recognizers, i.e., the configuration used with the standard version of FADE. One reason for this discrepancy is the coarser step size of the training SNRs (ROR-FADE 6 dB; FADE 3 dB), as well as the multicondition training that might not improve the recognition performance for unmatched SNR training beyond the performance already achieved when sufficient training signals are available for matched SNR training. An optimum accuracy speed tradeoff (AST) was found for 240 train and 20
test sentences which showed the best trade-off with regard to simulation accuracy and required time.

The second benchmark showed median differences, i.e., systematic offsets, of 1 to 5 dB between ROR-FADE and FADE (Fig. 5). Thus, a correction of these systematic offsets independent of the masker seems not to be feasible. Predicting empirical SRTs with ROR-FADE was accurate for the stationary icra1m masker, i.e. a systematic offset not more than 1 dB, but not for the fluctuating masker (approx. 5 dB offset). There, the difference to the empirical SRT was about the same as the difference between the simulated SRTs and FADE, which implies that more training data would reduce the differences. The standard deviations of the simulated SRTs for 120 and 240 training sentences (below 1.2 dB for each masker) were close to or below empirical test-retest accuracies (Hochmuth et al., 2015; Kollmeier et al., 2015). The confidence intervals (Fig. 5) were symmetric to the median for each masker such that random errors cancel out when sufficient repetitions are simulated. Therefore it seems that 120 training sentences are sufficient for simulations with maskers that have little envelope fluctuations (i.e., silence or stationary maskers), or when the absolute threshold interferes with the masker’s audibility (Fig. 5 and 6).

The simulations with ROR-FADE of the unaided hearing impaired simulations (Fig. 6) showed little differences to the FADE simulations and could also predict the empirical SRTs with a high accuracy ($R^2 \geq 0.96$, RMSE $< 5$ dB). Interestingly, ROR-FADE provided more accurate predictions using 120 training sentences than with 240 training sentences. This, however, is only an effect of the number of training sentences since FADE typically predicts SRTs lower than the measured SRTs. In addition, using fewer training sentences results in an increase of the predicted SRTs (Fig. 4 and 5).

In the third benchmark ROR-FADE was used to simulate hearing impairment together with hearing aid algorithms (Fig. 7). These simulations did not introduce further offsets than observed in the previous benchmarks. That is, the bias across all maskers (silence, stationary and fluctuating) and hearing aid algorithms (linear amplification, compression amplification, and compression amplification with a noise-suppressing beamformer) resembled the median differences found with stationary maskers (see Fig. 5 and 6). Even though fluctuating maskers were used for these simulations, the differences were not as large as before. This might be due to the interplay between the fluctuating masker and hearing impairment, or due to the interplay between hearing aid algorithms and hearing impairment, or both. Probably, the hearing aid algorithms also interfere with the fluctuations of the maskers: Inaudible parts of the mixed speech and noise signal are amplified and compressed. Consequently, the mixed signals become more spectro-temporally flat by removing spectro-temporal gaps (similar to signal representations with elevated absolute thresholds). This simplified the training of the automatic speech recognition system since less statistic fluctuations needed to be covered by the GMMs. Note, though, that this also prevents using the spectro-temporal gaps to recognize speech. The comparison with the empirical measurements showed that ROR-FADE predicted on average lower than measured SRTs, but with a high accuracy ($R^2 \geq 0.9$, RMSE $< 5$ dB).

In all, the benchmark experiments showed that ROR-FADE simulates similar SRTs as FADE, albeit there were larger differences between the FADE versions when a fluctuating masker was used. Additionally, ROR-FADE could predict the empirical outcomes with nearly the same accuracy as found with FADE, but with the exception of fluctuating maskers with assumed normal hearing. The third benchmark that was based on the data from Schädler et al. (2020) showed that the differences between the FADE versions were smaller for simulations with hearing impairment and signal processing in contrast to simulations with normal hearing and unprocessed signals. Therefore, it seems to be plausible that ROR-FADE can provide accurate predictions of aided speech recognition performance, especially when taking into account that Schädler et al. (2020) used FADE to accurately predict SRTs ($R^2 = 0.94$, RMSE $= 4.2$ dB) and benefits ($RMSE = 2.7$ dB; $R^2 = 0.82$) for a diverse group of listeners with and without hearing impairment.

### 4.3 Experiment 2: Hearing aid benefit

While a comparison between the unmodified FADE and ROR-FADE is possible for the benchmark conditions discussed so far, this is not possible for the black-box hearing aid benefit predictions performed in Experiment 2 since not enough recorded speech material processed with the respective hearing aid algorithm was available to run the unmodified FADE. Also, no appropriate empirical data was available to directly compare the ROR-FADE predictions with SRT-data for individual hearing impaired subjects for the unaided and aided case. Hence, the expected accuracy of the predictions can only be assessed indirectly based on the following facts:

a) The expected deviation between ROR-FADE and the unmodified FADE is small (i.e., less than 5 dB for fluctuating maskers and less than 2 dB for stationary maskers, see Fig. 5), and the difference between ROR-FADE and empirical data was small for listeners with normal hearing (5 dB, see Fig. 5), and also for listeners with hearing impairment (RMSE less than 5 dB, see Fig. 6).

b) The accuracy of the unmodified FADE for predicting individual hearing aid benefit is very high as being inferred from Schädler et al. (2020) in conditions with a highly controllable hearing aid (Master hearing aid, MHA Herzke et al., 2017).

Assuming that the MHA processing is comparable to the processing of the actual black-box hearing aids employed here, there is good evidence that ROR-FADE is able to perform a precise individual patient performance prediction in accordance with the general aim of the current paper. Moreover, the simulations performed for Experiment 2 can be assessed by considering the plausibility of the simulations in light of the current literature as follows:

The data of Schädler et al. (2020) included two listeners with hearing loss close to the Bisgaard profile N3. The
benefits found for one of these listeners in a spatially separated condition was 17 dB in silence, 8 dB in the stationary (icra1m) masker, and 8 dB in the fluctuating (icra5-250m) maskers (see the ADM & compressive condition Schädler et al., 2020, Fig. 6). In Figure 8, the largest simulated benefits with hearing aids A and C were 17 dB in silence, 10 dB in stationary masker (icra1m), and 8 dB with the fluctuating masker (icra5-250m). Thus, the simulations with hearing aids A and C differed only by up to 2 dB in each condition from the empirical data. Other studies contribute to ROR-FADE’s plausibility by reporting on equivalent aided SRTs in stationary and fluctuating maskers when speech and masker were co-located (Herzke et al., 2012, here aided SRT stationary: -8.0 dB SNR; fluctuating -8.7 dB SNR), benefits by spatially separating speech and noise when using hearing aids (Ahlstrom et al., 2009; Neher et al., 2009), or benefits found in fluctuating maskers (Luts et al., 2010, 6 to 7 dB).

Apart from these studies, other implications for the plausibility of the simulated aided listening conditions exist. For example, the benefits in the co-located condition were higher with the fluctuating masker than with the stationary masker. This is plausible, since fluctuations allow for glimpsing (Cooke, 2006), which can be facilitated by linear amplification. Then again, an inverse trend was observed when speech and noise were separated, i.e., the benefits with the stationary masker were higher. This is also plausible, due to the speech-like modulations of the fluctuating masker that interfere with the beamformer and/or noise suppression algorithms. Similar trends were observed for all three hearing aids and for both fittings. Therefore, it is also likely to simulate similar SRTs and benefits when repeating the study.

Taken together, the simulations with ROR-FADE seem to yield plausible outcomes, especially when taking into account the studies and benchmark experiments. These simulations show the feasibility of ROR-FADE to predict the aided performance of individual listeners with different types of real hearing devices and they could demonstrate the performance differences across three types of commercial hearing devices as well. Further studies need to be performed to test these predictions that are derived from realistic measurements with the devices and a prediction model validated with other data before.

### 4.4 Applications of ROR-FADE

FADE was successfully modified to drastically reduce simulation time in conditions where only real time signal processing is available. Yet, the benchmarks showed that random and static offsets between the FADE versions remain, especially when fluctuating maskers are used. This implies, that the simulation accuracy might decrease when the acoustic scene becomes more complex. In such cases, a more conservative approach with ROR-FADE might be required. For example, more training sentences and a finer grid of training SNRs could be used when complexity increases. In such cases, a preliminary fine tuning of ROR-FADE should be conducted, e.g., by determining a required accuracy, or by selecting optimal ASTs for each parameter and masker. As a general recommendation, standard FADE should be used when the external constraints allow it. Nevertheless, it is assumed that the parameter space exploited in the current paper should provide a sufficient guideline for most applications.

Possible fields of application for ROR-FADE include hearing aid development, the selection of individual hearing aids, or the optimization of hearing aid fittings with respect to speech recognition performance. ROR-FADE can provide guidance for the development of hearing aids by indicating which algorithm provides benefits and which one does not. This might even be used in more complex, but realistic and relevant acoustic environments, such as, e.g., in cafeterias, bars, or supermarkets. Similarly, a set of hearing aids which promise the highest benefits could be selected for an individual to accelerate the selection process and possibly also to increase the acceptance of hearing aids. This approach could be extended to provide a first fit of the hearing aids as proposed by Völker et al. (2018). However, since FADE currently does not take into account overall presentation levels, or rather loudness, its applicability to automatic hearing aid fitting is limited. Yet, ROR-FADE could be paired with a loudness model (e.g., Moore and Glasberg, 2004, 2007; Oetting et al., 2016) to predict if a proposed fitting method is acceptable.

An additional benefit of using ROR-FADE is its direct applicability to all languages which have a matrix sentence test (i.e., more than 20). This facilitates to objectively compare different devices used in different maskers and different languages. Therefore, differences in required properties of hearing aids in dependence on the language would become apparent as long as they relate to those acoustic properties predictable by FADE. For example, the benefit provided by hearing aids with the same setting for tonal languages like Mandarin or Cantonese might differ significantly from benefits found for non-tonal languages like English or German. Note, however, that FADE appears to utilize the respective optimum speech features in each language since the deviation between simulations and empirical data is the same in a tonal language (Mandarin: empirical -11.2 dB (Hu et al., 2018), FADE: -12.7 dB, data not published) as in German, Polish, Russian, and Spanish SRTs (Schädler et al., 2016a).

### 5 Conclusions

The most important findings and implications of this study are:

1. The FADE version modified to facilitate accurate simulations with fewer train and test data than the original FADE (ROR-FADE) can be used with real hearing devices with unknown properties (i.e., signal processing black boxes) to simulate SRTs with about 30 minutes of mixed signals of matrix sentence tests. This enables in-situ objective evaluations of hearing aids or prototypes thereof.

2. The deviation from predictions with the unmodified FADE approach in the proposed configuration (120 or 240 train and 20 test sentences per SNR) was found to be small (1 to 2 dB) in many cases, and as large
as 4 to 5 dB in a strongly fluctuating noise masker. The flexibility of the approach allows to reduce the deviation (to 1.5 dB) by increasing the simulation time (to about 2.5 hours with 960 train sentences per SNR).

3. The modified approach enables an individual, non-intrusive hearing aid benefit prediction based on a limited amount of recorded signals using the respective hearing aid as “black box” device. Even though a validation of this approach with comparison between prediction and actual individual performance is still open, the accuracy of the unmodified FADE for this purpose (Schädel et al., 2020) and the plausibility of the prediction demonstrated here hint towards the potential of this approach for model-based hearing aid fitting. Likewise, the development of hearing devices might benefit from ROR-FADE.

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