Abstract—In this paper, we address the generalization of deep neural network (DNN) based speech enhancement to unseen noise conditions for the case that training data is limited in size and diversity. To gain more insights, we analyze the generalization with respect to (1) the size and diversity of the training data, (2) different network architectures, and (3) the chosen features. To address (1), we train networks on the Hu noise corpus (limited size), the CHiME 3 noise corpus (limited diversity) and also propose a large and diverse dataset collected based on freely available sounds. To address (2), we compare a fully-connected feed-forward and a long short-term memory (LSTM) architecture. To address (3), we compare three input features, namely logarithmized noisy periodograms, noise aware training (NAT) and the proposed signal-to-noise ratio (SNR) based noise aware training (SNR-NAT). We confirm that rich training data and improved network architectures help DNNs to generalize. Furthermore, we show via experimental results and an analysis using t-distributed stochastic neighbor embedding (t-SNE) that the proposed SNR-NAT features yield robust and level independent results in unseen noise even with simple network architectures and when trained on only small datasets, which is the key contribution of this paper.

Index Terms—Deep neural networks, generalization, speech enhancement, noise reduction, input features

I. INTRODUCTION

Speech is used by humans for communication, e.g., to exchange ideas and emotions. Speech is therefore an essential component of many applications that have emerged from increasingly powerful personal electronic devices such as hearing aids, mobile phones and virtual assistants. Many devices are mobile and are therefore often used in noisy environments. As a consequence, the microphones do not only capture the desired speech signal but also unwanted background noises. Background noises are known to degrade the perceived quality of speech and are able to deteriorate the speech intelligibility. To restore the quality and potentially also the intelligibility, speech enhancement algorithms are leveraged. In this paper, we consider single-channel speech enhancement algorithms that allow the enhancement of noisy recordings obtained from a single microphone or the output of a spatial filter.

Single-channel speech enhancement has been a topic of research for many decades and various approaches have been introduced in the literature [1]–[7]. Many approaches use a time-frequency representation, e.g., the short-time Fourier transform (STFT), to enhance noisy input signals. Often, the enhancement can be represented by a multiplication of the noisy Fourier coefficients with a real-valued gain function. Conventional speech enhancement algorithms are often derived in a statistical framework. The complex Fourier coefficients are modeled by parametric probability density functions (PDFs) whose parameters are given by the speech power spectral density (PSD) and the noise PSD. The statistical framework then allows the derivation of statistically optimal estimators of the clean speech coefficients. Depending on the statistical assumptions about speech and noise, different gain functions are obtained [2], [8]–[10]. The unknown parameters of the speech PDF and the noise PDF, i.e., the speech PSD and the noise PSD, are estimated using algorithms based on statistical and signal processing models [2], [11]–[14]. Most of these algorithms are based on the assumption that the background noise changes more slowly than speech. This makes conventional speech enhancement algorithms robust to many acoustic conditions, which is why they provide good results in moderately varying noise types, i.e., noises where the amplitude changes slowly in the STFT bands. This applies for example for passing cars on a busy street. However, they lack the ability to track very fast changes of the background noise such as the cutlery in a restaurant or sudden speech bursts in a babbble scene. Consequently, transient noises are often not suppressed by conventional approaches.

The shortcomings of conventional speech enhancement algorithms motivated the use of machine-learning (ML) algorithms for speech enhancement. Various ML algorithms have been considered, e.g., codebooks [15]–[17], hidden Markov models and Gaussian mixture models [3], [18]–[21] and non-negative matrix factorization (NMF) [4], [5], [22], [23]. Today, deep neural networks (DNNs) have become a widely used tool for speech enhancement [6], [7], [24]–[29]. DNNs potentially allow the approximation of any non-linear function on a limited range of the input space [30]. This flexibility allows DNNs to be used in various ways for speech enhancement. In [31]–[34], parts of conventional speech enhancement algorithms, e.g., the speech PSD estimator or the noise PSD estimator, have been replaced by DNNs. Other approaches try to find a mapping from the noisy observation or features extracted from it to a masking function [35]–[37]. Suitable target functions and their effect on the enhancement performance have been analyzed in [35], [37], [38]. Instead of using a masking function, the clean speech coefficients have also been used as target of a DNN in many approaches [6], [7], [36], [39]. For this, various architectures of DNNs have been employed, e.g., feed-forward networks [6], [7], recurrent neural networks [24] including long short-term memory cells [37], [40]–[42], generative adversarial networks [43], [44], convolutional neural networks [27], [29], [45] and WaveNet based approaches [28], [46].

Many studies show that DNN based approaches yield higher performance than conventional speech enhancement approaches. One of the concerns is however the generalization to unknown acoustic conditions [26], [47]–[51]. On the one
In this paper, we focus on the generalization of DNN based speech enhancement algorithms and consider the three approaches depicted in Fig. 1. All approaches predict a gain function, i.e., regression approaches as proposed in [7] are not considered. The input features are different though. The approach depicted in the first row of Fig. 1 serves as a baseline and uses only the periodogram of the noisy input as feature. The second approach is similar to dynamic NAT presented in [48], [49]. As shown in Fig. 1, an estimate of the noise PSD is appended to the noisy periodogram features. Similar to [49], we use the conventional noise PSD estimator proposed in [14] to continuously update the noise PSD estimate. Last, we propose SNR-NAT features, which are related to the \textit{a priori} signal-to-noise ratio (SNR) and the \textit{a posteriori} SNR as defined in [2]. The corresponding SNRs are based on speech and noise PSD estimates obtained from noisy speech using conventional enhancement approaches [13], [14] as shown in the third row of Fig. 1. We show that noise datasets such as the Hu noise corpus [55] or the CHiME 3 noise corpus [56], [57] are either not sufficiently large or diverse to train a general model using the standard logarithmized periodogram or NAT features. We propose a larger and more diverse training corpus using sounds from \texttt{freesound.org}. It is used to confirm that increasing the size and the diversity of the noise data increases the robustness of DNN based enhancement models. The key contribution of this paper is that the generalization to unseen noise can also be addressed by using more informed features based on conventional signal processing approaches, i.e., using the proposed SNR-NAT features. We show that using the SNR-NAT features, the training is more robust to insufficient training such that even a small and less diverse dataset allows the model to generalize to unseen acoustic conditions. Further, we show that the DNN based enhancement scheme becomes independent of the input’s signal level if SNR-NAT features are employed.

For better understanding, we analyze and compare the statistics of the logarithmized periodogram, the NAT features and the SNR-NAT features. For this analysis, we use histograms and t-distributed stochastic neighbor embedding (t-SNE) for visualization [58]. The results show that the SNR-NAT features are less dependent on changes of the overall level and the background noise. Further, also the internal representation of the DNN is less dependent on the background noise if SNR-NAT features are employed instead of NAT features.

This paper extends our previous papers [59], [60] and provides for a more in depth analysis and evaluation. It has the following structure. In Section II we recapitulate the conventional speech and noise PSD estimators presented in [13], [14], [61] that are used to extract speech PSD and noise PSD as shown in the second and third row of Fig. 1. These estimates are later used in the NAT and SNR-NAT features which are described in Section III. Furthermore, the DNN based enhancement methods and the used network architectures are also presented in Section III. Section IV describes the evaluation and the training data which is used for the evaluation in Section V and the analysis in Section VI. Section VII concludes this paper.

II. CONVENTIONAL SPEECH AND NOISE PSD ESTIMATION

This section gives an overview of conventional speech enhancement in the STFT domain. The first part describes the steps required to enhance a signal in the STFT domain and the following sections consider conventional speech and noise PSD estimation algorithms. Here, the conventional noise PSD estimator which is based on [14], [61] is recapitulated first. Last, the speech PSD estimator is considered which uses cepstral smoothing as described in [13]. The speech and the noise PSD estimates of these conventional algorithms also form the basis of the NAT and SNR-NAT features used for the DNN-based enhancement scheme discussed in Section III.

A. Speech enhancement in the STFT domain

This section describes how speech can be enhanced in the STFT domain which is leveraged by various speech enhancement algorithms. The presented procedure also applies to the DNN based enhancement method presented in Section III. The STFT of a time-domain signal is obtained by splitting it into overlapping segments and taking the Fourier transform of each segment after a tapered spectral analysis window has
been applied. This procedure results in the time-frequency representation of the clean speech signal $S_{k,ℓ}$, the noise signal $N_{k,ℓ}$ and the noisy input signal $Y_{k,ℓ}$. Here, $k$ is the frequency index and $ℓ$ is the segment index. In this work, a segment length of 32 ms is used and the segment shift is set to 16 ms, i.e., the segments overlap by 50%. The considered input signals are sampled using a sampling rate of 8 kHz and consequently, the segment length corresponds to 256 samples and the segment shift to 128 samples. Further, we use a square-root Hann window for spectral analysis.

The enhancement takes place in the spectral domain and can be expressed using a gain function $G_{k,ℓ}$ which is applied to the noisy spectra. Mathematically, the estimated clean speech coefficients are given by

$$\hat{S}_{k,ℓ} = \max(G_{k,ℓ}Y_{k,ℓ}, G_{\text{min}}),$$

where $G_{\text{min}}$ is a lower limit of the gain function. This lower limit has been found helpful to reduce artifacts and disturbances in the enhanced speech signal [62]. In this work, we choose to set $G_{\text{min}}$ to $-20$ dB. A well known gain function is the Wiener filter

$$G_{\text{Wiener}} = \frac{\Lambda_{s,ℓ}}{\Lambda_{s,ℓ} + \Lambda_{n,ℓ}},$$

where $\Lambda_{s,ℓ}$ and $\Lambda_{n,ℓ}$ denote the speech PSD and the noise PSD, respectively. The Wiener filter is the minimum mean-squared error (MMSE) optimal estimator of the clean speech coefficients if the speech coefficients $S_{k,ℓ}$ and the noise coefficients $N_{k,ℓ}$ are additive, uncorrelated and follow a complex circular-symmetric Gaussian distribution. The former two assumptions are based on the physical properties of the interaction of multiple sound sources, i.e., speech and noise. The latter assumption is often justified by the central limit theorem which can be applied due to the Fourier sum which needs to be evaluated for obtaining the spectral coefficients [63] Chapter 4]. The speech PSD $\Lambda_{s,ℓ}$ and the noise PSD $\Lambda_{n,ℓ}$ are estimated blindly from the noisy observation using [13], [14], [61]. Both algorithms are summarized in the following sections.

After estimating the clean speech coefficients, the clean speech spectra $\tilde{S}_{k,ℓ}$ are transformed back to the time-domain. A synthesis window is applied to the resulting time-domain segments where again a square-root Hann window is employed. After that, the enhanced clean speech signal is obtained using an overlap-add procedure.

### B. Noise PSD Estimation

In this work, we use the algorithm presented in [14], [61] to estimate the noise PSD. This estimator allows the tracking of moderate changes in the background noise such as passing cars. However, it cannot track transient disturbances like the cutlery noise in a restaurant. In the remainder of this section, the algorithm is briefly introduced.

The noise PSD estimator in [13], [61] models the complex noisy coefficients under the hypotheses of speech presence $H_1$ and speech absence $H_0$ using parametric distributions. Given $H_0$, the noisy observations equal $Y_{k,ℓ} = N_{k,ℓ}$ while under $H_1$ the noisy coefficients are given by $Y_{k,ℓ} = S_{k,ℓ} + N_{k,ℓ}$ which is a physically plausible assumption. The speech coefficients $S_{k,ℓ}$ and the noise coefficients $N_{k,ℓ}$ are assumed to follow a complex circular-symmetric Gaussian distribution. Accordingly, the likelihoods under the hypotheses $H_0$ and $H_1$, i.e., $f(Y_{k,ℓ}|H_0)$ and $f(Y_{k,ℓ}|H_1)$, are also modeled using Gaussian distributions. The speech presence probability (SPP) is defined as the posterior probability $P(H_1|Y_{k,ℓ})$ which can be obtained using Bayes’ theorem. The posterior used in [14], [61]

$$P(H_1|Y_{k,ℓ}) = \left(1 + (1 + \xi_{H_1}) \exp \left( -\frac{|Y_{k,ℓ}|^2}{\Lambda_{n,ℓ}^0 \Lambda_{n,ℓ}^{-1} + \xi_{H_1}^2} \right) \right)^{-1},$$

has been derived under the assumption that the prior $P(H_1) = P(H_0) = 1/2$. Here, a fixed SNR $\xi_{H_1}$ is used which is interpreted as the local SNR that is expected if the hypothesis $H_1$ holds [14], [61]. The likelihood models $f(Y_{k,ℓ}|H_0)$ and $f(Y_{k,ℓ}|H_1)$ have been used to formulate a speech detection problem in [14]. By minimizing the total risk of error [14], the optimal value $\xi_{H_1} = -15$ dB has been found.

The posterior probability $P(H_1|Y_{k,ℓ})$ is used to estimate the noise periodogram as

$$|\hat{N}_{k,ℓ}|^2 = (1 - P(H_1|Y_{k,ℓ}))|Y_{k,ℓ}|^2 + P(H_1|Y_{k,ℓ})\hat{\Lambda}_{n,ℓ}^{-1}.$$  

The estimated noise periodogram $|\hat{N}_{k,ℓ}|^2$ is smoothed temporally to obtain an estimate of the noise PSD as

$$\hat{\Lambda}_{n,ℓ} = (1 - \alpha_{\text{SPP}}^{(\text{fix})})|\hat{N}_{k,ℓ}|^2 + \alpha_{\text{SPP}}^{(\text{fix})}\hat{\Lambda}_{n,ℓ}^{-1},$$

where $\alpha_{\text{SPP}}^{(\text{fix})}$ is a fixed smoothing constant. This estimator can be implemented in a speech enhancement framework by evaluating (3), (4) and (5) for each frequency band $k$ when a new segment $ℓ$ is processed. If the noise PSD is strongly underestimated, the SPP in (7) is overestimated, i.e., it is close to 1. As a result, the noise periodogram in (4) may no longer be updated. To avoid such stagnations, the SPP is set to a lower value if it has been stuck at 1 for a longer period of time [14], [61].

### C. Speech PSD Estimation

For estimating the speech PSD $\Lambda_{s,ℓ}$, the temporal cepstrum smoothing (TCS) approach described in [13] is employed. In contrast to the commonly used decision-directed approach [2], this approach causes less isolated estimation errors, which may be perceived as annoying musical tones. In this section, we recapitulate the main concepts of this algorithm.

Under the assumption that the spectral noise and speech coefficients follow a complex circular-symmetric Gaussian distribution, the limited maximum likelihood estimator is given by [2]

$$\hat{\Lambda}_{s,ml}^{k,ℓ} = \hat{\Lambda}_{s,ℓ}^{k,ℓ} \max \left( \frac{|Y_{k,ℓ}|^2}{\Lambda_{n,ℓ}^0 - 1, \xi_{\text{min}}} \right),$$

where the max$(\cdot)$ operator in combination with $\xi_{\text{min}}$ is used to avoid negative speech PSDs and numerical issues in the following steps. For the practical applicability, $\Lambda_{n,ℓ}$ has been replaced by its estimate $\hat{\Lambda}_{n,ℓ}.$
The maximum likelihood estimate is transformed to the cepstral domain via
\[
\hat{\Lambda}_{s,ml}^k = \text{IDFT}\{\log(\hat{\Lambda}_{s,ml}^k)\},
\]
(7)
where \(q\) is the quefrency index and \(\text{IDFT}(\cdot)\) denotes the inverse discrete Fourier transform. In the cepstral domain, speech can be represented by using only a few coefficients: The speech spectral envelope, which reflects the impact of the vocal tract filter, is represented by the lower coefficients with \(q < 2.5\) ms whereas the speech spectral fine structure, i.e., the fundamental frequency and its harmonics, is approximated by a single peak among the high cepstral coefficients. This peak is also referred to as pitch peak. The compact representation of speech is exploited by the TCS approach by using a quefrency and time dependent smoothing factor \(\alpha_{q,\ell}\) to smooth \(\hat{\Lambda}_{s,ml}^k\) as
\[
\hat{\Lambda}_{s,\ell}^k = (1 - \alpha_{q,\ell})\hat{\Lambda}_{s,ml}^k + \alpha_{q,\ell}\hat{\Lambda}_{s,\ell-1}^k.
\]
(8)

For the cepstral coefficients that are associated with speech only little smoothing is applied while the remaining cepstral coefficients are strongly smoothed. Accordingly, \(\alpha_{q,\ell}\) is set close to 0 for the lower cepstral coefficients and close to 1 for the high coefficients. In voiced segments, the \(\alpha_{q,\ell}\) in close vicinity to the cepstral pitch peak are changed to values close to 0.

The cepstrally smoothed speech PSD \(\hat{\Lambda}_{q,\ell}^k\) is transformed back to the spectral domain as
\[
\hat{\Lambda}_{k,\ell}^s = \exp\left(\text{DFT}\{\hat{\Lambda}_{q,\ell}^k\} + \frac{\gamma}{2}\right).
\]
(9)
As the smoothing in the cepstral domain results in a biased estimate \([64]\), the correction term \(\gamma/2\) is added where \(\gamma \approx 0.5772\ldots\) is the Euler constant. In \([13]\), it has been argued that the bias of computing the expected value of a spectral quantity following a Gaussian distribution in the logarithmic domain amounts to the Euler constant. Due to the smoothing, the estimate in the cepstral domain is between an instantaneous value and the expected value. A more rigorous analysis of the bias is given in \([64]\).

III. DNN Based Speech Enhancement

In this section, the DNN based speech enhancement algorithms used in this paper are presented. The first part of this section, considers the two DNN architectures analyzed in this paper. We consider a feed-forward network and an long short-term memory (LSTM) based network \([40]\). After that, the input features are considered, which are used for both networks.

A. Network Architectures

Similar to the conventional speech enhancement scheme described in Section II-A, the DNN based enhancement schemes also operate in the STFT domain. In this paper, the DNN’s task is to estimate an IRM \([35]\) using the features \(v_{k,\ell}\) extracted from the noisy input signal. The IRM has been proposed in \([35]\) and depends on the speech periodogram \(|S_{k,\ell}|^2\) and the noise periodogram \(|N_{k,\ell}|^2\). It can be defined as
\[
G_{k,\ell}^{\text{IRM}} = \frac{|S_{k,\ell}|^2}{|S_{k,\ell}|^2 + |N_{k,\ell}|^2}.
\]
(10)

Fig. 2. Block diagram of the DNN architectures employed in this study. The upper diagram shows the feed-forward network, while the lower diagram shows the LSTM network.

While during training the actual speech and noise periodogram are available to compute the IRM, a trained DNN is used to predict the IRM during processing. The predicted IRM is used to estimate the clean speech coefficients \(\hat{S}_{k,\ell}\) as in \([1]\). Other targets such as ideal binary masks \([35]\) or complex ideal ratio masks \([39]\) are not considered and could potentially exhibit a different behavior than the employed IRM target.

The IRM is estimated using two different network architectures. Both networks differ in size and style to make it possible to provide an analysis on how the proposed features perform for different neural networks. The first architecture has a feed-forward structure. The input features are passed through three fully-connected hidden layers where each layer comprises 1024 rectifying linear units (ReLUs) \([65]\) as shown in the upper diagram Fig. 2. The last layer contains 129 units to match the dimensionality of the STFT spectra after removing the mirror spectrum. Sigmoid non-linearities are used to enforce the output to be in the same range as the IRM, i.e., between zero and one.

The second architecture uses recurrent layers and is based on LSTM cells \([40]\). Here, the input features are passed through three layers comprising 512 LSTM cells. Similar to the feed-forward network, the final layer is a fully connected layer with 129 sigmoid units. The architecture is shown in the lower diagram of Fig. 2.

The parameter choice has been inspired by other networks used in the literature, e.g., \([7]\, [37]\, [42]\, [66]\), and resembles loosely the structures of those architectures.

B. Features

In this section, the input features that are used in combination with both DNN architectures are considered.

First, the logarithmized noisy periodogram features are tackled. This feature forms the basis of the NAT features, which are described afterwards. The feature vector for the logarithmized periodogram of the noisy input coefficients has
the mirror spectrum, i.e., $K$ is denoted by $\cdot$ enhancement in unseen acoustic conditions [48]–[50], [54].

As this is a potentially challenging task, NAT has been used [67], [68], e.g., to obtain cepstral representations [69], [70], which may change results slightly. However, in this study we focus on the presented compact features for conciseness.

Given only the log-spectral coefficients of the noisy observation, the DNN learns from the training data to distinguish between the desired speech signal and the background noise. As this is a potentially challenging task, NAT has been proposed to improve the robustness of DNN based speech enhancement in unseen acoustic conditions [48]–[50], [54].

For this, NAT appends a logarithmized noise PSD estimate to the logarithmized noisy periodogram. The feature vector of the logarithmized noisy PSD is given by

$$v_{\ell}^{(\text{PSD})} = [\log(\Lambda_{1,\ell}), \ldots, \log(\Lambda_{K,\ell})]^T.$$ \hspace{1cm} (12)

The NAT features are then given by the concatenation of $v_{\ell}^{(\text{Per})}$ and $v_{\ell}^{(\text{PSD})}$ for each frame $\ell$ as

$$v_{\ell}^{(\text{NAT})} = \left[ (v_{\ell}^{(\text{Per})})^T, (v_{\ell}^{(\text{PSD})})^T \right]^T.$$ \hspace{1cm} (13)

Using NAT features, i.e., appending the noise PSD to the noisy log-spectra, doubles the dimensionality of the input features which results in a 258-dimensional vector. In our experiments, the noise PSD is estimated using the approach described in Section II-B i.e., based on [14], [61]. The noise PSD is estimated from noisy data both during training and testing such that the network learns the estimation characteristics of the employed noise PSD estimator.

In contrast to the NAT features, where the noise PSD is appended to the noisy input periodogram, we proposed to use the noise PSD for normalization to obtain so-called SNR-NAT features [59], [60]. The SNR-NAT features correspond to logarithmized versions of the $a$ priori SNR $\xi_{k,\ell} = \Lambda_{k,\ell}^n/\Lambda_{k,\ell}^n$ and the $a$ posteriori SNR $\gamma_{k,\ell} = |Y_{k,\ell}|^2/\Lambda_{k,\ell}^n$. Both features can also be stacked in feature vectors as

$$v_{\ell}^{(\text{prior})} = [\log(\xi_{1,\ell}), \ldots, \log(\xi_{K,\ell})]^T,$$ \hspace{1cm} (14)

$$v_{\ell}^{(\text{post})} = [\log(\gamma_{1,\ell}), \ldots, \log(\gamma_{K,\ell})]^T.$$ \hspace{1cm} (15)

Further, also the combination of both SNR based features is considered which yields the SNR-NAT features

$$v_{\ell}^{(\text{SNR-NAT})} = \left[ (v_{\ell}^{(\text{prior})})^T, (v_{\ell}^{(\text{post})})^T \right]^T.$$ \hspace{1cm} (16)

The noise PSD $\Lambda_{k,\ell}^n$ is estimated again using the approach from Section II-B [14], [61]. The speech PSD is estimated as described in [13] and Section II-C. For similar reasons to the NAT features, the speech and the noise PSD are estimated from noisy data both during training and testing. The $a$ priori SNR and the $a$ posteriori SNR have been previously used in data-driven speech enhancement approaches [71]–[74], but these approaches did not use DNNs. More interestingly, we show in [59], [60] that the SNR-NAT features result in more robust DNN based speech enhancement algorithms especially if the size or the diversity of the training data is limited.

For the feed-forward architecture described in Section III-A a temporal context is added to all input features. For this, a super-vector $\tilde{v}_{\ell}$ is created which stacks the features of the current frame and the features from three previous frames

$$\tilde{v}_{\ell} = [v_{\ell}^T, \ldots, v_{\ell-3}^T]^T.$$ \hspace{1cm} (17)

This increases the dimensionality of the input features by a factor four, i.e., the dimensionality is raised from 129 to 516 (logarithmized periodogram) or from 258 to 1032 (NAT and SNR-NAT), respectively. The resulting feed-forward network has 2.7 million weights, if the log periodogram features are used, and 3.3 million weights, if NAT or SNR-NAT is used.

Due to their recurrent structure, LSTM networks are able to include context on their own and therefore, no additional context is used for this network type. Hence, the input dimensionality for the LSTM networks remains 129 (logarithmized periodogram) or 258 (NAT and SNR-NAT), respectively. The LSTM network has 5.6 million weights, if the log periodogram features are used, and 5.8 million weights, if NAT or SNR-NAT features are used.

### IV. Experimental Setup

The DNN based speech enhancement algorithm described in Section III is trained using three noise corpora: the Hu noise corpus [55] with the extension presented in [75], the CHiME 3 noise corpus [56], [57] and a custom noise set which has been created from sound packs available from the freesound.org website. We refer to the Hu corpus and its extension just as Hu corpus to keep the naming scheme simple. The noise sets vary in the amount of audio data and the variety of the noise material as described below.

The Hu noise corpus [55] comprises 100 non-speech sounds and the extension [75] adds another 15 sounds. The sounds cover many different acoustic environments, but the recordings are generally short and their duration often does not exceed ten seconds. The total duration of the sound material included in this corpus is about 14 minutes.

The background noises included in the CHiME 3 challenge [56], [57] comprise four different acoustic environments: a ride on a bus, the interior of a cafe, a pedestrian area and a street junction. These scenarios have been captured using a tablet equipped with six microphones. As we consider single-channel speech enhancement algorithms in this work, only the recordings of the first microphone are employed. Due to the low number of acoustic environments included in the CHiME 3 noise corpus, also the diversity of the noise corpus is rather limited. However, the duration of the recordings is long and the total amount of noise data in this corpus amounts to about 8.5 hours.

The last dataset is constructed from freely available sounds taken from the freesound.org website. The links to the sound packs used to create this data set are given in Table I. From the sound recordings in these packs, we discard all sounds whose
It is ensured that about noise which also affects the overall level of the noisy signal. The domain peak level of the clean speech signal is varied between different overall levels of the input signal. For this, the time-corruption, the input SNR of each sentence is varied between real-world data. To make the DNN aware of different levels of initialization period is not excluded from the training data. As a would be strongly impacted by initialization artifacts, if the training data. Using the first two seconds for initialization is feature extraction, the initialization period is removed from the is randomly chosen for each sentence. To allow the noise PSD estimator described in Section II-B [14], [61] to adapt to the background noise, a two second long initialization period is added in the beginning of the noisy sentence. After the feature extraction, the initialization period is removed from the training data. Using the first two seconds for initialization is not an issue in many speech communication applications like hearing aids or telecommunications. In contrast, the training would be strongly impacted by initialization artifacts, if the initialization period is not excluded from the training data. As a consequence, the training data would not be representative for real-world data. To make the DNN aware of different levels of corruption, the input SNR of each sentence is varied between −10 dB and 15 dB. Additionally, also level variations are included in the training data to allow the DNN to adapt to different overall levels of the input signal. For this, the time-domain peak level of the clean speech signal is varied between −26 dB and −3 dB before being corrupted by the background noise which also affects the overall level of the noisy signal. It is ensured that about 10 % of the training data contain only noise to enable the DNN to reject noise only regions.

The data described above is split into a training set and a validation set. A portion of 15 % of the data is used as a validation set and the remaining data is used for training. To initialize the parameters of the respective DNNs, the Glorot method described in [77] is used. After that, the parameters are trained by minimizing the squared-error between the true and the predicted IRM using stochastic gradient descent. The error function is given by the squared error

\[ J = \sum_k \sum_\ell (G_{k,\ell}^{\text{IRM}} - G_{k,\ell}^{\text{IRM}})^2. \]  

The learning rate is reduced from 0.4 to 0.1 over the training epochs using an exponential decay as \( LR = \max(0.4 \cdot 0.95^{E-1}, 0.1) \). The symbols \( LR \) and \( E \) denote the learning rate and the current epoch, respectively. The feed-forward networks have been trained for a maximum of 50 epochs while for the LSTM networks the maximum number of epochs was set to 20. Only the model with the lowest validation error is used for testing which is similar to using an early stopping strategy. All networks have been trained using Keras 2.2.4 and Tensorflow 1.13.1.

### V. Instrumental Evaluation

In this section, we analyze how the input features affect the performance of the DNN based speech enhancement algorithms using instrumental measures. For this, we employ extended short-time objective intelligibility (ESTOI) [78], perceptual objective listening quality analysis (POLQA) [79], as well as, segmental speech SNR (SegSSNR) and segmental noise reduction (SegNR) described in [80]. ESTOI is an instrumental measure of the speech quality, while POLQA is a measure of the speech quality. Generally, the difference between the enhanced signal and the noisy signal, i.e., the improvement over the noisy signal, is shown for ESTOI and POLQA to simplify the comparison of the algorithms. SegSSNR and SegNR are used to measure the amount of speech distortion and noise reduction of the respective processing scheme.

For testing, we use noises taken from NOISEX-92 database [81] and freesound.org. We ensure that none of these noise types have been used during training, i.e., all noise types used for testing are unseen in terms of the noise realization. Depending on the used training data also some of the realizations can be different. From the NOISEX-92 database, we include the “factory 1”, “f16” and “destroyerops” environment. Additionally, amplitude modulated versions of NOISEX-92’s white and the pink noise are included. Both noises are sinusoidally modulated with a frequency of 0.5 Hz and a modulation depth of 0.5. From the freesound.org database we include the last four noise types. These are an aircraft interior noise (freesound.org/s/188810), a babble noise (freesound.org/s/886553), an overpassing propeller plane (freesound.org/s/115387), traffic noise (freesound.org/s/252216) and a vacuum cleaner (freesound.org/67421).

The speech material is taken from the TIMIT test set [76] which also ensures that the speech material is different from the training. We select 64 sentences spoken by male speakers and 64 sentences spoken by female speakers. The 128 sentences have been recorded from 20 different speakers. The sentences are artificially corrupted by the noises described above. This is done in two different ways.

First, we analyze how the overall level of the input signal influences the performance of the DNN based speech enhancement approaches. For this, we keep the input SNR fixed at a

---

**TABLE I**

| username       | list of ids               |
|----------------|---------------------------|
| Robinhood76    | 3238, 3246, 3667, 3668, 3729, 3830, 3840, 3870, 3873, 3971, 3979, 3980, 4024, 4025, 4026, 4036, 4058, 4065, 4149, 4364, 5589 |
| rutgermuller   | 20158                     |
level of 5 dB and set the peak-level of all 128 sentences to different fixed values. Each sentence hence appears with a peak level of $-40$ dB, $-24$ dB, $-18$ dB, $-12$ dB and $-6$ dB in the text set. Again, the peak level is adjusted before the sentence is corrupted by the background noise. Most levels are in the range that has also been used in the training data, whereas the peak level $-40$ dB is an extreme case which has not been seen during training. The results for this evaluation are discussed in Section V-A.

Second, we conduct an experiment where all sentences are corrupted by all noise types at input SNRs ranging from $-5$ dB to $20$ dB. For this experiment the peak level of each sentence randomly varied between $-26$ dB and $-3$ dB, i.e., the same range used for training. The results of this experiment are shown in Section V-B.

### A. Evaluation Over the Input Level

In this section, we analyze the influence of the input level on the performance of the considered speech enhancement methods. Fig. 3 depicts the results for both DNN architectures, three different trainings sets and three different input features. Additionally, the results for a conventional speech enhancement algorithm are shown which is based on Wiener filtering and the speech and noise PSD estimations methods described in Section II-A.

The left three columns in Fig. 3 show the results for the feed-forward network. Both ESTOI and POLQA show that the performance of the DNN based enhancement schemes depends on the overall level of the input signal if periodogram features or NAT features are used. In general, the performance of these two enhancement schemes degrades with lower input levels. Furthermore, the SegNR indicates that the noise reduction becomes worse with decreasing level of the input signal. At the same time, also the speech distortion decreases as indicated by the increasing SegSSNR. This indicates that the DNN based speech enhancement algorithms reduce less noise if the periodogram and NAT features are employed. The scores for the conventional enhancement scheme and the proposed SNR-NAT features are virtually the same over all input levels. This indicates that in contrast to the periodogram and NAT features, the proposed SNR-NAT features are virtually independent of the overall level.

If LSTM networks are employed, the level dependence becomes weaker if periodogram and NAT features are employed. However, this dependency is still measurable and results in lower performance if the level of the input signal drops. Especially, for an input level of $-40$ dB that has not been included in the training data, a small decrease in performance can be observed. For the proposed SNR-NAT features, the performance is again virtually the same, i.e., independent of the input level.

These results also give a preview on the general performance of the considered algorithms, which we will discuss in more detail next.

### B. Evaluation Over the Input SNR

Similar to Section V-A also here, the artificially corrupted sentences are enhanced by the DNN based speech enhancement algorithms which are trained using different features. In contrast to Section V-A we analyze the performance of the approaches in dependence of the input SNR. Figure 4 shows the improvements in POLQA and ESTOI in dependence of the input SNR, the employed training dataset and the employed input feature. Further, also the absolute values for the SegSSNR and SegNR measures are shown again. All measures are averaged over all noise types and again, the conventional approach is included as a baseline.

Figure 4 shows that the performance of the DNN based approach depends on the training dataset. If the logarithmized periodogram or NAT is used as input feature, the performance is considerably lower for the Hu noise corpus (low amount of data) is employed. In general, the SegNR is lower in comparison to the SNR-NAT features and at the same time the SegSSNR is slightly higher. This indicates again that the DNN based speech enhancement schemes suppress less noise, if non-robust features are used in combination with a low amount of noise training data. Using the larger and more diverse training datasets such as CHiME 3 or the proposed collection from freesound.org improves the performance of the periodogram and NAT features in terms of POLQA and ESTOI. If the feed-forward DNN is considered, the performance of NAT and SNR-NAT features are about the same, while the periodogram features yield slightly lower scores. If the LSTM network is used, both the periodogram and NAT features yield slightly higher scores in POLQA and ESTOI than the proposed SNR-NAT features.

This analysis shows that for the proposed SNR-NAT features, the performance of the DNN based speech enhancement approach is more robust for the considered features and training methods when only limited training data are available. In fact, the performance using SNR-NAT is comparable for all three considered training datasets. A dataset with limited diversity, i.e., the CHiME 3 noise corpus, has a smaller negative impact on instrumental measures. Hence, it is possible to train well performing DNNs using a dataset with limited diversity if sufficiently powerful features are used, e.g., NAT or SNR-NAT, or if sufficiently complex network types are used, e.g., LSTMs. From these observations, we conclude that (1) a well performing model in terms of instrumental measures can be trained independently of the feature if appropriate training data are available and (2) that the normalization considerably improves the robustness of the DNN based speech enhancement approach in unseen acoustic conditions if insufficient training data are available.

These findings are analyzed in more depth in the next section. There, we will also show that a network that performs well in terms of averaged instrumental measures, still might struggle in unseen noise conditions.

### VI. Analysis

In this section, we analyze and discuss the results obtained in Section V. First, we apply t-SNE [58] on the input features, the output of the internal of the internal representation of the second last layer and the enhanced speech signals. The resulting plots are used to analyze the effect of the different
training data and features on the generalization of DNN based speech enhancement algorithms. Further, we consider the masks predicted by the DNN based speech enhancement methods for some examples taken from the test signals used in Section V, i.e., for unseen noise conditions.

A. T-SNE Analysis

In this section, we analyze the input features NAT and SNR-NAT and the internal representation of the feed-forward and LSTM networks using t-SNE [58]. T-SNE is a method that embeds high dimensional vectors in a low dimensional space. For this experiment, we extract NAT features $v^{(NAT)}$ and SNR-NAT features $v^{(SNR-NAT)}$ from artificially corrupted speech signals, where no additional context is added to the feature vectors. Two sentences of a male speaker and a female speaker are used where the speech signals are normalized to a maximum peak level of $-6$ dB. After this, the sentences are corrupted by seven different background noise types at an SNR of 5 dB which have not been seen during training. T-SNEs have been obtained using the original implementation of the tree-based accelerated t-SNE algorithm described in [82] with a perplexity of 50 and a threshold $\theta = 0.5$. For all datasets the algorithm was run for 1000 iterations and the t-SNE embedding converged for all datasets. The result of the t-SNE analysis is depicted in the scatter plot shown in Fig. 5. Each point in the figure corresponds to a high dimensional feature vector embedded in a low dimensional space.

As one part of the NAT feature vector contains the noise PSD estimate, the features highly depend on the noise type. This can also be seen from the embeddings in Fig. 5, where vectors extracted from the same noise type end up in the same cluster. The overlap between the cluster is quite small and most of the clusters are easily separable. In contrast to the NAT features, the embeddings for the SNR-NAT features do not show strong clusters depending on the noise type. Instead all embeddings are mixed together and it is not easily possible to separate the data points based on the background noise type. From this, we conclude that the SNR-NAT features are considerably less dependent on the background noise type. This independence of the background noise may be an important property of the SNR-NAT features to train data driven speech enhancements models that generalize well to unseen noise types.

The same audio files have been used to extract the embeddings shown in Fig. 6 and Fig. 7. In contrast to Fig. 5, the embeddings have been computed from the second last layer of a trained network, i.e., an internal representation of the neural network, and the absolute magnitudes of the enhanced speech coefficients. Fig. 6 shows the results for the feed-forward network, while Fig. 7 shows the results for the LSTM network. In both figures, the upper two rows show the embeddings for the internal representation and the last two rows depict the embedding for the enhanced speech signal. Furthermore, both figures depict the embeddings for different training data sets, which are shown in the different columns.

The first row of Fig. 6 shows the embeddings of the internal representations of the feed-forward network, which has been trained using NAT features. Interestingly, also the deep internal
Fig. 4. POLQA improvements, ESTOI improvements, SegSSNR and SegNR for feed-forward based (left columns) and LSTM based (right columns) speech enhancement algorithms in dependence of the input SNR, input feature and training dataset. The input level is randomly varied between $-24$ dB and $-3$ dB. The results of a conventional speech enhancement approach are shown for comparison.

Fig. 5. T-SNE of different input features representation of the network appears to be dependent on the noise type as indicated by clusters that form for each noise type similar to Fig. 5. Contrarily, the internal representation that is obtained when using the SNR-NAT features, depicted in the second row of Fig. 6 does not show this behaviors and no clustering can be observed. These observations can be made for all training data sets.

The third and the fourth row in Fig. 6 shows the embeddings for the estimated clean speech coefficients. A strong clustering of the enhanced speech coefficients with respect to the noise type is thought to be an undesired effect because the estimated clean speech coefficient should be independent of the background noise. Still, some dependence on the noise type is to be expected as the noise is only attenuated and not completely suppressed in our experiments. The embeddings of estimated speech coefficients shown in the third row, which result when using the NAT features, show some dependence on the training data. Some noise type dependent clustering is observable if the Hu corpus is employed for training, but the data points are much more mixed as compared to the layer output. Still, the somewhat stronger dependence of the estimated clean speech coefficients on the noise type might explain the lower scores in ESTOI and POLQA shown in Fig. 4. The embeddings for the CHiME 3 dataset and the freesound.org dataset are quite similar. In general, no obvious dependence on the noise type is visible and the scores obtained for both training datasets are similarly high. The embedding of the enhanced speech coefficients obtained when using the SNR-NAT features are generally mixed. Interestingly, the embeddings seem to be more clustered when using the CHiME 3 dataset and the freesound.org dataset for training. However, this type of clustering does not appear to have a relationship to the ESTOI and POLQA scores shown in Fig. 4.

Fig. 7 shows similar embeddings as Fig. 6 but here the LSTM network has been used instead of the feed-forward network. One of the most clearly visible differences to Fig. 6 is shown in the first row. The embeddings of the internal representations are less clustered if the network is trained on the CHiME 3 dataset or the freesound.org dataset using NAT features. If the Hu corpus is used in combination with NAT features for training, the internal representation is still clustered similar to the feed-forward network. This indicates that the LSTM networks are able to find an internal representation that is more independent of the noise type.
Looking at the embeddings of the estimated clean speech coefficients that have been obtained using NAT features, it appears that these are more clustered if the network is trained on the Hu corpus \cite{55} in comparison to the other training datasets. Again, this is in line with the observation that the network yields the lowest scores in ESTOI and POLQA as shown in Fig. 4. For the SNR-NAT features, the observations obtained from the LSTM network are similar to the feed-forward network.

From these observations, we follow that NAT features are noise dependent. Further, their usage also leads to a noise dependent internal representation for feed-forward networks. If an LSTM network is used and the training data is sufficiently diverse, i.e., the CHiME 3 corpus \cite{57} or the freesound.org is used, a noise independent internal representation can be learnt. Contrarily, the proposed SNR-NAT features are independent of the noise type and hence, also lead to a internal representation that is independent of the background noise. This can be observed for both the employed feed-forward network and LSTM network. Therefore, the SNR-NAT are more robust to issues in the design of the training data and applications with small amounts of data available. Further, SNR-NAT features are scale-invariant.

**B. Predicted Masks in Unseen Noise Conditions**

In this section, examples are used to demonstrate the advantages and disadvantages of the different input features. For this, a single speech signal is corrupted by F16 noise and vacuum cleaner noise at an SNR of 0 dB. The first four seconds of the noisy input signals contain only noise. The signal is processed using the LSTM based speech enhancement networks that have been trained using the previously described input features. Figure 8 and 9 shows the resulting masks that result from the respective networks.

Both noise types are relatively stationary and should not pose a problem to the speech enhancement algorithms. But the masks clearly show that these noise types can be challenging for the DNN based speech enhancement algorithms. If the Hu corpus and NAT features are used for training, the resulting network is unable to cope with these unseen noise types. Instead of reducing the noise, the mask shows values close to 0 dB at random positions in the noise only region at the beginning of the signals. This behavior is in line with the reduced noise reduction and increased SegSSNR, which has been observed in Section \textsection{V} for the networks trained with the Hu corpus. The random behavior of the mask in noise regions is clearly audible and degrades the signal quality in noise only regions drastically. Using the proposed SNR-NAT features, the network correctly reduces the noise in regions where only noise is present. Consequently, a lot less artifacts and random openings of the mask are observable in the enhanced signal and, as a result, the quality of the processed signal is considerably better with the proposed SNR-NAT features.

Even though the behavior is not as extreme as for the Hu corpus, such errors can also be observed for more complex training datasets when the NAT features are used. Despite the high scores in POLQA and ESTOI for networks trained on the CHiME 3 dataset and the proposed \texttt{freesound.org} dataset with NAT features, there are still artifacts observable in the noise only regions. If trained on the \texttt{freesound.org} corpus, the network modulates speech-like sounds into the noise as
shown in Figure 8 if NAT features are used. In the vacuum cleaner noise shown in Figure 9, several spots can be observed in lower frequencies for the mask of the network trained on the CHiME 3 dataset despite only noise being present. Even though the modulations are less extreme, it can be verified using sound examples, that the observed artifacts are still audible. Contrarily, the background noise is much smoother when the proposed SNR-NAT features are employed leading to robust results in practical use cases.

The examples used in Fig. 8 and Fig. 9 are also available as sound example:\[\text{https://www.inf.uni-hamburg.de/en/inst/ab/sp/publications/}
\text{las2021-robust-se-rr.html}\]

Additionally, the website contains excerpts of the real evaluation set of the CHiME 3 challenge 56, 57 and a video recording from our lab, which have been processed using the algorithms considered here. In contrast to the signals used here, the CHiME 3 and the lab video examples on the website are real recordings, i.e., speech and noise have not been artificially mixed. The sound examples show that the conclusions from Section VII and this section also apply to real signals.

VII. CONCLUSIONS

In this paper, we addressed the generalization of DNN based speech enhancement algorithms to unseen noise. For this, we analyzed the impact of different input features, different training data sets and different network architectures. Furthermore, we propose SNR-NAT features and a noise dataset based on sounds collected from freesound.org to improve the robustness of DNN based speech enhancement algorithms.

Our findings indicate that diverse training data that are severely limited in size, e.g., the Hu corpus 55, may severely limit the generalization of speech enhancement networks, especially if simplistic features are used. Contrarily, a large dataset results in a better generalization, even if the diversity is limited, as for the CHiME 3 corpus 57 which consists of only four noise environments. However, we showed that for noise sounds that do not follow the typical spectral envelope of the CHiME 3 noise environments, like a vacuum cleaner or F16 noise, the performance may still be unsatisfactory. Generally, a large and diverse dataset such as the proposed dataset constructed from sounds from freesound.org is required to train a speech enhancement network that generalizes well to unseen conditions.

Further, we show that the proposed SNR-NAT features lead to more robust networks even if training data limited in size and diversity are used. This result is confirmed also by an analysis via t-SNE which shows less noise-specific clustering for SNR-NAT features than for periodogram or NAT features. The t-SNE analysis shows that the LSTM network is able to disentangle the dependency on the noise type of periodogram and NAT features if sufficient training data are available. Using SNR-NAT features as input feature, however, the internal representation becomes noise independent also for...
less complex network types such as the feed-forward network. The examples in Fig. [8] and Fig. [9] further show that also LSTM networks benefit from SNR-NAT features especially in noise only regions and ensure that also unseen noises are correctly suppressed.

REFERENCES

[1] S. Boll, “Suppression of acoustic noise in speech using spectral subtraction,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 27, no. 2, pp. 113–120, Apr. 1979.

[2] Y. Ephraim and D. Malah, “Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 32, no. 6, pp. 1109–1121, Dec. 1984.

[3] Y. Ephraim, “A Bayesian estimation approach for speech enhancement using hidden Markov models,” IEEE Transactions on Signal Processing, vol. 40, no. 4, pp. 725–735, Apr. 1992.

[4] M. N. Schmidt and J. Larsen, “Reduction of non-stationary noise using a non-negative latent variable decomposition,” in IEEE Workshop on Machine Learning for Signal Processing (MLSP), Cancun, Mexico, Oct. 2008, pp. 486–491.

[5] N. Mohammadiha, P. Smaragdis, and A. Leijon, “Supervised and unsupervised speech enhancement using nonnegative matrix factorization,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 21, no. 10, pp. 2140–2151, Oct. 2013.

[6] X. Lu, Y. Tsoa, S. Matsuda, and C. Hori, “Speech enhancement based on deep denoising autoencoder,” in Interspeech, Lyon, France, Aug. 2013.

[7] X. Lu, J. Du, R. L. Dai, and C. H. Lee, “A regression approach to speech enhancement based on deep neural networks,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 23, no. 1, pp. 7–19, Jan. 2015.

[8] C. Breithaupt, M. Krawczyk, and R. Martin, “Parameterized MMSE spectral magnitude estimation for the enhancement of noisy speech,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Las Vegas, NV, USA, Apr. 2008, pp. 4037–4040.

[9] J. Erkelenz and R. Heusdens, “Tracking of nonstationary noise based on data-driven recursive noise power estimation,” Audio, Speech, and Language Processing, IEEE Transactions on, vol. 16, no. 6, pp. 1112–1123, Aug. 2008.

[10] R. C. Hendriks, R. Heusdens, and J. Jensen, “Log-spectral magnitude MMSE estimators under super-Gaussian densities,” in Interspeech, Brighton, United Kingdom, 2009, pp. 1319–1322.

[11] S. Cohen and B. Berdugo, “Noise estimation by minima controlled recursive averaging for robust speech enhancement,” IEEE Signal Processing Letters, vol. 9, no. 1, pp. 12–15, Jan. 2002.

[12] R. Martin, “Noise power spectral density estimation based on optimal smoothing and minimum statistics,” IEEE Transactions on Speech and Audio Processing, vol. 9, no. 5, pp. 504–512, Jul. 2001.

[13] C. Breithaupt, T. Gerkmann, and R. Martin, “A novel a priori SNR estimation approach based on selective cepstro-temporal smoothing,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Las Vegas, NV, USA, Apr. 2008, pp. 4897–4900.

[14] T. Gerkmann and R. C. Hendriks, “Unbiased MMSE-based noise power estimation with low complexity and low tracking delay,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 4, pp. 1383–1393, May 2012.

[15] S. Srinivasan, J. Samuelsson, and W. B. Kleijn, “Codebook driven short-term predictor parameter estimation for speech enhancement,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 14, no. 1, pp. 163–176, Jan. 2006.

[16] T. Rosenkranz and H. Puder, “Improving robustness of codebook-based noise estimation approaches with delta codebooks,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 4, pp. 1177–1188, May 2012.

[17] Q. He, F. Bao, and C. Bao, “Multiplicative update of auto-regressive gains for codebook-based speech enhancement,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 25, no. 3, pp. 457–468, Mar. 2017.

[18] H. Sameti, H. Shielkhzadeh, L. Deng, and R. L. Brennan, “HMM-based strategies for enhancement of speech signals embedded in nonstationary noise,” IEEE Transactions on Speech and Audio Processing, vol. 6, no. 5, pp. 455–455, Sep. 2006.

[19] D. Burshtein and S. Gannot, “Speech enhancement using a mixture-maximum model,” IEEE Transactions on Speech and Audio Processing, vol. 10, no. 6, pp. 341–351, Sep. 2002.
