DNN-Based Multi-Frame MVDR Filtering for Single-Microphone Speech Enhancement

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Abstract

Multi-frame approaches for single-microphone speech enhancement, e.g., the multi-frame minimum-variance-distortionless-response (MVDR) filter, are able to exploit speech correlations across neighboring time frames. In contrast to single-frame approaches such as the Wiener gain, it has been shown that multi-frame approaches achieve a substantial noise reduction with hardly any speech distortion, provided that an accurate estimate of the correlation matrices and especially the speech interframe correlation vector is available. Typical estimation procedures of the correlation matrices and the speech interframe correlation (IFC) vector require an estimate of the speech presence probability (SPP) in each time-frequency bin. In this paper, we propose to use a bi-directional long short-term memory deep neural network (DNN) to estimate a speech mask and a noise mask for each time-frequency bin, using which two different SPP estimates are derived. Aiming at achieving a robust performance, the DNN is trained for various noise types and signal-to-noise ratios. Experimental results show that the multi-frame MVDR in combination with the proposed data-driven SPP estimator yields an increased speech quality compared to a state-of-the-art model-based estimator.

Index Terms: Robust Mask Estimation, Deep Neural Network, Single-Microphone Speech Enhancement, MVDR Filtering

1. Introduction

In many hands-free speech communication systems such as hearing aids, mobile phones and smart speakers, ambient noise may degrade the speech quality and intelligibility of the recorded microphone signals. Hence, several single- and multi-microphone speech enhancement approaches have been proposed [6, 7, 8, 9, 10]. Typical single-microphone speech enhancement systems use a real-valued spectro-temporal gain, e.g., the Wiener gain (WG) [11], to the short-time Fourier transform (STFT) coefficients of the noisy microphone signal to obtain an estimate of the clean speech signal. A disadvantage of these methods is that stronger noise reduction typically goes hand-in-hand with increased speech distortion.

In contrast to single-frame approaches, multi-frame approaches [6, 7, 8, 9, 10] apply a complex-valued filter to the noisy STFT coefficients and are able to take into account the speech correlation across consecutive time frames. Similarly to the minimum-variance-distortionless-response (MVDR) beamformer and the minimum-power-distortionless-response beamformer (MPDR) for multi-microphone speech enhancement [12, 13], multi-frame MVDR (MFMVDR) and multi-frame MPDR (MFMPDR) filters have been proposed for single-microphone speech enhancement [6, 7, 10]. These multi-frame filters require an estimate of the noisy or noise correlation matrix and the speech interframe correlation (IFC) vector in each time-frequency (TF) bin. When oracle estimates of these quantities are available, it has been shown in [6, 12] that the MFMVDR and MFMPDR filter achieve a large noise reduction and hardly any speech distortion in contrast to the WG. However, it has also been shown that the speech enhancement performance is very sensitive to estimation errors of the IFC vector [12].

In [7] a maximum likelihood (ML)-based approach has been proposed to estimate the (highly time-varying) speech IFC vector from the noisy microphone signals. The ML estimator requires an estimate of the noise power spectral density (PSD), which in turn requires an estimate of the speech presence probability (SPP) in each TF bin. Several model-based SPP estimators have been proposed [15, 14], where the approach in [14] is based on the assumption that the speech and noise STFT coefficients are uncorrelated, complex Gaussian distributed random variables.

In recent years, data-driven supervised learning-based approaches have gained a lot of attention in a multitude of applications, including single-microphone speech enhancement [15, 16, 17, 18, 19, 20]. A common approach is to estimate real-valued TF masks, which are applied to the noisy STFT coefficients. To this end, different masks have been used as the learning target, e.g., ideal binary masks (IBMs) [15], ideal ratio masks (IRMs) [16], and complex ideal ratio masks (cIRMs) [17]. Furthermore, mask-based approaches have been recently proposed to estimate the speech and noise correlation matrices that are required by multi-microphone speech enhancement approaches such as the MVDR beamformer or the generalized eigenvalue beamformer [21, 22, 23, 24].

Inspired by the approach in [23], in this paper we propose to use a data-driven SPP to estimate the required correlation matrices and speech IFC vector for the MF MVDR and MF MPDR filter. More in particular, we use a bidirectional long short-term memory (BLSTM) [25] deep neural network (DNN) to estimate speech and noise masks from the noisy STFT magnitudes, from which two different SPP estimates are derived. Aiming at achieving a robust performance, the DNN is trained on the TIMIT [26] and NOISEX92 [27] datasets using 4 noise types and a signal-to-noise-ratio (SNR) range from -5 to 20 dB. Experimental results for non-matched noise types show that the proposed DNN-based SPP estimates improve the speech quality as predicted by objective measures compared to the model-based SPP estimate [14], where the MF MVDR filter outperforms the MF MPDR filter.

2. Signal Model

We consider an acoustic scenario with one speech source and ambient noise, recorded using a single microphone. In the STFT domain, the noisy microphone signal is given by

\[ Y(k,l) = X(k,l) + N(k,l), \]

(1)

where \( X(k,l) \) denotes the speech component and \( N(k,l) \) denotes the noise component at the \( k \)-th frequency bin and the \( l \)-th time frame.

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Multi-frame speech enhancement approaches \cite{5,8,10} estimate the speech component by applying a finite impulse response filter with \(N\) taps to the noisy STFT coefficients, i.e.,

\[
\hat{X}(k,l) = \sum_{n=0}^{N-1} H_n(k,l) Y(k,l-n),
\]

where \(\hat{\circ}\) denotes an estimate of \(\circ\), \(H_n(k,l)\) denotes the \(n\)-th filter coefficient, and \(^\dagger\) denotes the complex-conjugate operator. Using vector notation, (1) and (2) can be written as

\[
y(k,l) = \pi(k,l) + n(k,l),
\]

\[
\hat{X}(k,l) = H^H(k,l)y(k,l),
\]

where \(H\) denotes the Hermitian operator and the \(N\)-dimensional vectors \(h(k,l)\) and \(y(k,l)\) contain the filter coefficients and \(N\) consecutive STFT coefficients, i.e.,

\[
h(k,l) = [H_0(k,l), H_1(k,l), \ldots, H_{N-1}(k,l)]^T,
\]

\[
y(k,l) = [Y(k,l), Y(k,l-1), \ldots, Y(k,l-N+1)]^T.
\]

This is analogous to multi-channel beamforming approaches \cite{4,5,11} by considering the FIR filter as a spatial filter and frames as microphone inputs. Since all frequency bins are treated individually, in the remainder of this paper we omit the frequency index \(k\).

Assuming that the speech and noise components are uncorrelated, the noisy correlation matrix \(\Phi_y(l)\) is defined similarly as \(\Phi_x(l)\) in \cite{6}. It has been proposed to exploit the speech correlation across consecutive time frames by separating the speech component into a correlated and an uncorrelated part, i.e.,

\[
x(l) = \gamma_c(l) X_c(l) + \gamma_u(l) X_u(l),
\]

where the (time-varying) normalized speech IFC vector \(\gamma_u(l)\) describes the correlation between the current and previous time frames and is defined as

\[
\gamma_u(l) = \frac{\mathcal{E}\{x(l)X^\dagger(l)\}}{\mathcal{E}\{X(l)X^\dagger(l)\}} = \phi_x(l)\gamma_u(l),
\]

with the vector \(\mathcal{E}\{\cdot\}\) selecting the first column of \(\Phi_x(l)\) and \(\phi_x(l) = \mathcal{E}\{X(l)\}\) the speech PSD. The uncorrelated speech component \(X_u(l)\) is treated as an interference and is hence included in the undesired signal vector \(u(l)\), i.e.,

\[
u(l) = x(l) + n(l).\]

The noisy correlation matrix from (7) can hence be rewritten as

\[
\Phi_y(l) = \phi_x(l)\gamma_u(l)\gamma_u^H(l) + \Phi_u(l),
\]

with \(\Phi_u(l) = \Phi_y(l) - \Phi_x(l)\) the undesired correlation matrix. Note that since \(\gamma_u(l)\) is fully correlated with itself, the first element of the speech IFC vector \(\gamma_u(l)\) in (12) is equal to 1, such that the first element of the uncorrelated speech vector \(X_u(l)\) is equal to 0. As a consequence, \(\phi_x(l) = \mathcal{E}\{X(l)\}\) is 0 and \(\gamma_u(l) = \phi_x(l)\).

4. Parameter Estimation

In practice, the performance of the MFVMDR and the MFMFDR filter obviously depends on how well the time-varying correlation matrices \(\Phi_y(l)\) and \(\Phi_u(l)\) as well as the speech IFC vector \(\gamma_u(l)\) can be estimated from the noisy microphone signals. In \cite{12} it has been shown that the performance of the MFMFDR filter is very sensitive to estimation errors of the speech IFC vector. Whereas estimating the noise correlation matrix \(\Phi_u(l)\) is rather straightforward, estimating the noise correlation matrix \(\Phi_n(l)\) and the speech IFC vector \(\gamma_u(l)\) is not so trivial. The parameter estimation and multi-frame filtering process is depicted in Fig. 7. The following subsections discuss the estimation of the correlation matrices and the speech IFC vector.

4.1. Correlation Matrix Estimation

To estimate the time-varying noise correlation matrix \(\Phi_n(l)\) from the noisy microphone signals, we apply the recursive smoothing procedure presented in \cite{28}, where the smoothing factor for each TF bin depends on the SPP and a smoothing constant \(\alpha_n\), i.e.,

\[
\Phi_n(l) = \lambda_n(l)\Phi_n(l-1) + (1 - \lambda_n(l))y(l)y^H(l),
\]

\[
\lambda_n(l) = \alpha_n + (1 - \alpha_n)\text{SPP}(l).
\]
The SPP estimate \( \hat{X} \) is estimated by the DNN, i.e.,

\[
\hat{X}(l) = \lambda_0 \hat{X}(l-1) + (1-\lambda_0) y(l) y^H(l). \tag{22}
\]

To improve the numerical stability when inverting these correlation matrices, we perform regularization using diagonal loading as in \((6,7)\), with regularization parameter \( \delta = 0.04 \).

To estimate the SPP in \((19)\) for each TF bin, we consider two approaches. As the reference approach, we use the state-of-the-art model-based approach from \((13)\), which assumes that the speech and noise PSDs can be derived, yielding the SPP estimate

\[
SPP_{i}(l) = \left(1 + \frac{P(\hat{H}_o)}{P(\hat{H}_i)} (1+\xi_{\hat{H}_i}(l)) e^{-\frac{|Y(l)|^2}{\sqrt{\phi_N(l)} + \delta}} \right)^{-1}, \tag{23}
\]

where \( P(\hat{H}_o) \) and \( P(\hat{H}_i) \) denote the prior probability of speech presence and absence, respectively, and the parameter \( \xi_{\hat{H}_i}(l) \) denotes the typical a-priori SNR encountered during speech presence.

Alternatively, in this paper we propose to exploit the capabilities of a BLSTM DNN to capture temporal dynamics in order to estimate a multi-target ideal noise mask, defined as \((24)\).

\[
M_X(l) = \frac{|X(l)|^2}{|X(l)|^2 + |N(l)|^2}, \quad M_N(l) = \frac{|N(l)|^2}{|X(l)|^2 + |N(l)|^2}, \tag{24}
\]

where \( M_X(l) \) denotes the speech mask and \( M_N(l) \) denotes the noise mask. It should be noted that \( M_X(l) + M_N(l) \) lie in \([0,1]\), and that \( M_X^2(l) + M_N^2(l) = 1 \). The DNN is expected to learn to associate speech-dominant TF bins with a large speech mask value and noise-dominant TF bins with a large noise mask value. We will investigate two different SPP estimates that can be derived from the masks estimated by the DNN, i.e.,

\[
SPP_{N1}(l) = \tilde{M}_X(l), \quad SPP_{N2}(l) = \frac{\tilde{M}_X(l)}{\tilde{M}_X^2(l) + \tilde{M}_N^2(l)}. \tag{25}
\]

The SPP estimates \( SPP_{N1}(l) \) only depends on the estimated speech mask, whereas \( SPP_{N2}(l) \) depends on both the estimated speech and noise mask. Since for the estimated masks generally \( M_X^2(l) + M_N^2(l) \neq 1 \), the SPP estimates \( SPP_{N1}(l) \) and \( SPP_{N2}(l) \) are typically different.

### 4.2. Speech IFC Vector Estimation

Similarly to \((14)\), the ML-based approach in \((7)\) estimates the speech IFC vector as

\[
\hat{\gamma}_x(l) = \frac{1 + \hat{\xi}(l)}{\xi(l)} \left( \frac{\hat{\gamma}_y(l) - \mu_{\gamma_n}}{\xi(l)} \right), \tag{26}
\]

where \( \mu_{\gamma_n} \) denotes the mean noise IFC vector, which can be computed based only on the overlap fraction and the window used for the STFT analysis. The noisy IFC vector \( \hat{\gamma}_y(l) \) is estimated from \( \hat{\Phi}_y(l) \) as in \((15)\). To estimate the a-priori SNR \( \xi(l) \), we apply the well-known decision-directed approach (DDA) \((29)\), i.e.,

\[
\hat{\xi}(l) = \frac{\lambda_{\text{DDA}}}{\phi_{\text{DDA}}(l-1)} \hat{X}(l-1) + (1-\lambda_{\text{DDA}}) \frac{|Y(l)|^2}{\phi_N(l)}, \tag{27}
\]

with weighting constant \( \lambda_{\text{DDA}} \) and \( \hat{X}(l-1) \) denoting the speech estimate of the previous frame. The DDA requires an estimate of the noise PSD, which can be computed from the estimated noise correlation matrix \( \hat{\Phi}_n(l) \) as \( \phi_N(l) = e^\Phi_n(l)e \).

### 5. DNN Training Process

Similarly to \((21,24)\), the DNN is trained to map features of the noisy microphone signal to the speech and noise masks defined in \((24)\). As input features, we use the magnitude of the noisy STFT coefficients \( |Y(l)| \). The DNN is composed of an input layer with 33 input nodes, a hidden BLSTM layer with 256 nodes for each direction, two hidden fully-connected layers with 513 nodes each, and an output layer with 66 nodes. The corresponding activation functions of the hidden and output layers are tanh, rectifying linear unit (ReLU), ReLU, and sigmoid, respectively, inherently restricting the mask estimates to \([0,1]\). This network architecture is inspired by the DNN used in \((21)\) and has been tested for various sets of hyperparameters.

The network weights are initialized using a uniform distribution \( U(-a,a) \), with \( a = \sqrt{6/((n_{in} + n_{out}))} \), and \( n_{in} \) and \( n_{out} \), the number of input and output neurons of the layer, respectively \((59)\). All bias values are initialized with 0. Dropout \((31)\) is used as a measure to counter overfitting, and the corresponding dropout probability is set to \( p_{\text{dropout}} = 0.4 \). To decrease the dynamic range of the input data and to stabilize the training process, we apply batch normalization to the input and before the activations of the hidden layers \((32)\). As loss function, we use the mean-squared error for both the speech and noise masks, i.e.,

\[
\frac{1}{L \times K} \sum_{l=0}^{L-1} \sum_{k=0}^{K-1} \left( \tilde{M}_X(k,l) - M_X(k,l) \right)^2 + \left( \tilde{M}_N(k,l) - M_N(k,l) \right)^2. \tag{28}
\]

To optimize the network parameters, we have used the ADAM optimizer with parameters as proposed in \((33)\), e.g., the learning rate is set to 0.001. If the \( l^2 \)-norm of a gradient is larger than 1, the gradient is divided by this norm.

From the training set (cf. Section 6.1), we randomly extract 20% of the utterances as the validation set. Training is stopped either after 100 epochs or after the validation loss as measured by \((28)\) has not decreased for 10 epochs. The DNN is implemented in PyTorch 1.0.1 \((34)\), and training and evaluation are performed on a multi-GPU system utilizing 3 NVIDIA GeForce GTX 1080 Ti graphics cards.

### 6. Experimental Results

In this section, we compare the speech enhancement performance of the MFMVDR and MFMPDR filters in \((10)\) and \((17)\) using the SPP
window is used both for STFT analysis and synthesis. The parameters As clean speech material, we have used 114 and 20 speakers from SPP estimate on both the speech IFC vector estimate smoothing constants, we use in [14], i.e., 

Since the speech interframe correlation is highly time-varying, we 6.2. Simulation Settings

From the computation of the objective performance measures. utterances for the evaluation set. For the evaluation set, 1 s of noise has been performed at the same SNRs. Please note that a single DNN

been used for the training set (car, factory, speechnoise, white) and for the evaluation set (factoryyl, operationsroomnoise). The DNN has been trained for the broadband SNRs \{-5, 0, 5, 10, 15, 20\}dB, and the evaluation has been performed at the same SNRs. Please note that a single DNN has been trained for all SNRs and not for each SNR separately. In total, 15072 utterances have been used for the training set and 240 utterances for the evaluation set. For the evaluation set, 1 s of noise has been appended at the beginning of each utterance, which is excluded from the computation of the objective performance measures. 

6.1. Dataset

As clean speech material, we have used 114 and 20 speakers from the TIMIT dataset [24] for the training and the evaluation set, respectively, ensuring that different speakers are used in both sets. The training set includes multiple utterances per speaker. The noisy microphone signals have been generated by adding scaled (randomly chosen) noise segments to the clean speech signals at a sampling frequency of 16 kHz. Different noise types from the NOISEX92 database [27] have been used for the training set (car, factory, speechnoise, white) and for the evaluation set (factoryyl, operationsroomnoise). The DNN has been trained for the broadband SNRs \{-5, 0, 5, 10, 15, 20\}dB, and the evaluation has been performed at the same SNRs. Please note that a single DNN has been trained for all SNRs and not for each SNR separately. In total, 15072 utterances have been used for the training set and 240 utterances for the evaluation set. For the evaluation set, 1 s of noise has been appended at the beginning of each utterance, which is excluded from the computation of the objective performance measures.

6.2. Simulation Settings

Since the speech interframe correlation is high-time varying, we employ an STFT with a high temporal resolution, i.e., a frame length of 4 ms and a frame shift of 1 ms, similarly as in [8][7][10]. A Hann window is used both for STFT analysis and synthesis. The parameters of the model-based SPP estimator SPP in [23] are set as proposed in [14], i.e., \(P(\hat{H}_t) = P(H_0) = 0.5\) and \(\xi(H_t) = 15\)dB. As recursive smoothing constants, we use \(\alpha_s = 0.98\) in [19], \(\lambda_v = 0.92\) in [22], and \(\lambda_{\text{DDA}} = 0.97\) in [27]. The MFMDVDR and MFMDPDR filters both use a filter length of \(N = 18\), such that correlations within a window of 21 ms can be exploited.

6.3. Results

For the 6 considered methods, Fig. [2] depicts the improvement in terms of perceptual evaluation of speech quality (PESQ) [35] and frequency-weighted segmental SNR (fwsSNR) [35] w.r.t. the noisy microphone signals as a function of the input SNR. For both performance measures, the clean speech signal has been used as the reference signal. The presented values are averaged over the 20 speakers and both noise types included in the evaluation set.

In terms of PESQ (Fig. [2a]), it can be observed that the MFMDPDR filter typically outperforms the MFMDVDR filter when using the model-based SPP estimate, whereas the MFMDVDR filter typically outperforms the MFMDPDR filter when using the DNN-based estimates. Comparing the performance of the DNN-based SPP estimate SPP\(_N^2\) to the model-based SPP estimate \(\hat{SPP}_{\text{R}}\), it can be observed for the MFMDPDR filter that using SPP\(_N^2\) leads to slightly larger improvements (except for 20 dB input SNR). For the MFMDVDR filter, it can be discovered that using SPP\(_N^2\) consistently yields significantly larger improvements than using \(\hat{SPP}_{\text{R}}\). Note that for the MFMDVDR filter, the SPP estimate influences only the speech IFC vector estimate, while for the MFMDVDR filter, the SPP estimate influences both the speech IFC vector as well as the noise correlation matrix estimate. Hence, the above results indicate that the proposed DNN-based SPP estimate \(\hat{SPP}_{\text{R}}\) yields both an improved a-priori SNR estimation accuracy as well as an improved noise correlation matrix estimation accuracy, especially in low-SNR scenarios.

Comparing the performance of both DNN-based SPP estimates, it can be observed that SPP\(_N^2\) consistently yields larger improvements than \(\hat{SPP}_{\text{R}}\) for both the MFMDPDR filter and the MFMDVDR filter, with differences increasing for higher input SNRs. This suggests that the noise mask estimate includes information that is not included in the speech mask estimate, benefiting the SPP estimation.

In terms of fwsSNR (Fig. [2b]), similar trends can be observed as for PESQ. In general, the differences between the model-based SPP estimate \(\hat{SPP}_{\text{R}}\) and the DNN-based estimate \(\hat{SPP}_{\text{N}^2}\) are slightly smaller than for PESQ. For an input SNR of 20 dB, a performance degradation can be observed for most considered methods, although this appears to be in contradiction with the PESQ result.

In summary, the MFMDVDR filter using the proposed data-driven SPP estimate \(\hat{SPP}_{\text{N}^2}\) consistently yields the highest performance in terms of PESQ, with the differences to the model-based SPP estimate remaining between 0.09 MOS and 0.18 MOS and decreasing for higher input SNRs.

7. Conclusion

In this paper we considered multi-frame approaches for single-microphone speech enhancement. Since both the MFMDVDR and the MFMDPDR filter require accurate estimates of time-varying correlation matrices and especially the speech IFC vector, in this paper we proposed a DNN-based estimator for speech and noise masks, using which two different SPP estimators are derived. The DNN is trained on multiple noise types at multiple SNRs to improve its generalization to unseen scenarios. We improve both the speech IFC vector estimation and the noise correlation matrix estimation. Experimental results demonstrate a higher objective speech quality when using the proposed SPP estimators instead of a model-based state-of-the-art estimator, with the MFMDVDR filter outperforming the MFMDPDR filter.
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