Subband Kalman Filtering with DNN Estimated Parameters for Speech Enhancement

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Abstract

In this paper, we present a novel deep neural network (DNN) assisted subband Kalman filtering system for speech enhancement. In the off-line phase, a DNN is trained to explore the relationships between the features of the noisy subband speech and the linear prediction coefficients of the clean ones, which are the key parameters in Kalman filtering. In the on-line phase, the input noisy speech is firstly decomposed into subbands, and then Kalman filtering is applied to each subband speech for denoising. The final enhanced speech is obtained by synthesizing the enhanced subband speeches. Experimental results show that our proposed system outperforms three Kalman filtering based methods in terms of both speech quality and intelligibility.

Index Terms: speech enhancement, subband Kalman filter, deep neural network, wavelet transform

1. Introduction

Speech enhancement aims at removing the background noise in noise-corrupted speech to improve its quality and intelligibility. It has been widely adopted in many applications including speech/speaker recognition, hearing aids and speech communication. During the past decades, researchers have proposed a variety of speech enhancement techniques.

Kalman filtering based speech enhancement was first proposed in [1] and has attracted researchers’ great interest because of its capability to enhance the time-domain and non-stationary speech signals. In this kind of method, the clean speech is often characterized as an autoregressive (AR) process and the Kalman filter is viewed as a linear MMSE estimator of the original clean speech. The performance of Kalman filtering is largely dependent on the estimation accuracy of the AR parameters, i.e., the linear prediction coefficients (LPCs) and the driving noise variance. Experiments demonstrated that the AR parameters estimated from the clean speech could achieve excellent performance [1]. However, the clean speech is not accessible in practice. As such, various estimation algorithms have been proposed to obtain the estimated parameters from noisy observations [2–5].

In recent years, the deep neural network (DNN) based signal processing methodology has largely advanced the research in speech enhancement. Compared with the unsupervised techniques, the DNN based approaches can achieve a better enhancement performance under the complex noise environment and/or low signal-to-noise ratio (SNR) conditions due to the powerful learning capability of the DNN. The earliest work employing DNN to learn the relationship between the magnitude spectra of the noisy speech and that of the clean speech was found in [6], where the enhanced speech is reconstructed with the DNN-estimated magnitude and the noisy speech’s phase. Subsequent works have utilized DNN to estimate the key parameters in traditional speech enhancement methods in order to improve the performances [7–9]. For example, in [9], the DNN is employed to estimate a complex ideal ratio mask (cIRM), which is then applied to the noisy spectrogram to suppress the additive noise. Recently in [10], we have proposed a DNN assisted Kalman filter for speech enhancement, where the DNN is trained to estimate the AR parameters for Kalman filtering. Although the performance is significantly improved compared with the iterative Kalman filtering [2], the high-frequency components of the enhanced speech are still degraded. One possible reason is that the noise does not affect the speech signal uniformly over the whole spectrum [11], while the Kalman filtering is not performed with respect to the different frequencies.

Subband analysis is widely adopted in speech processing such as speech coding. It has also been applied to speech enhancement to separately reduce the background noise in different subbands [12–15]. In [12], a subband Kalman filtering method was proposed, which applies low-order Kalman filters to the noisy subband speeches, and reconstructs the fullband clean speech by synthesizing the enhanced subband speeches. In [13], the authors proposed a multiband spectral subtraction, where the noisy speech spectrum is divided into several non-overlapping bands, and then spectral subtraction is performed independently in each band. The authors of [12] and [13] have shown that their subband methods yield better performances compared to their respective full-band counterparts [2, 16].

In light of the successes of the previous subband techniques, in this paper, we propose a novel DNN assisted subband Kalman filtering system for speech enhancement, where the noisy speech is divided into subband speeches using discrete wavelet transform (DWT). For each noisy subband speech, the DNN is employed for the estimation of AR parameters and the Kalman filter is then applied to obtain the enhanced subband speech. The inverse DWT (IDWT) is finally used to obtain the enhanced full-band speech. Compared with our previous work in [10], the proposed system performs denoising at each subband, and is thus able to not only suppress the background noise but also reduce the speech distortion in the enhanced speech, especially at higher frequencies. Computer simulations under various conditions show that the new system can yield better speech quality and intelligibility than previous Kalman filter based algorithms.

2. Proposed speech enhancement system

The overall block diagram of our DNN assisted subband Kalman filtering system is depicted in Fig. 1. It contains four...
parts: subband analysis, DNN based line spectrum frequencies (LSFs) estimation, Kalman filtering and subband synthesis. The details of each part are introduced in the following subsections.

![Block diagram of proposed speech enhancement system.](image)

### 2.1. Subband analysis and synthesis

Since the Kalman filter is viewed as a time-domain estimator, we adopt the DWT to directly decompose the time-domain noisy speech. This way can avoid the short-time Fourier transform (STFT) operation, which brings moderate distortion to the time-domain signal due to the necessary segmentation and windowing processes [15].

The DWT and IDWT are performed by a set of well-defined low-pass/high-pass filters together with a down/up-sampling process, which are regarded as distortionless analysis/synthesis for a time-domain signal. Taking a 2-level DWT for an example, in the first level, DWT decomposes a full-band signal $x$ into two subband signals with respect to the low and high frequency information components. In the next level, the decomposition operation is further applied to the low frequency subband signal, while the high frequency subband remains untouched. That is, with a $J$-level of DWT, we will obtain $J+1$ subband signals, as denoted by

$$x_b = DWT^J \{ x \}, \quad b = 1, 2, \cdots, J+1,$$

where $x_b$ is the $b$-th subband signal produced by DWT with $b$ denoting the subband index.

Similarly, for subband synthesis, the IDWT is adopted to reconstruct a full-band signal $\hat{x}$ from the subband signals, which is given by

$$\hat{x} = IDWT^J \{ x_b \},$$

where $x$ denotes the set of all subband signals $\{x_b\}_{b=1}^{J+1}$. The reconstructed signal $\hat{x}$ is identical to the original signal $x$ in the perfect reconstruction case.

### 2.2. Kalman filtering

While the noisy speech $y(n)$ is decomposed into subband speeches $\{y_b(n)\}_{b=1}^{J+1}$ in the subband analysis, Kalman filter is then applied to each noisy subband speech for denoising. To illustrate the Kalman filtering algorithm, we take an arbitrary noisy subband speech $y_b(n)$ for example, which is viewed as a mixture of the clean subband speech $s_b(n)$ and the additive noise $w_b(n)$,

$$y_b(n) = s_b(n) + w_b(n),$$

where $n$ is the discrete time index. The clean subband speech $s_b(n)$ is usually modelled as a dynamic process with the AR system,

$$s_b(n) = \sum_{i=1}^{p} a_{b,i} s_b(n - i) + v_b(n), \quad (4)$$

where $a_{b,i}$ are LPCs of the clean subband speech, $p$ the order of the model, and $v_b(n)$ the driving noise with variance $\sigma^2_v$.

To facilitate the Kalman filter presentation for speech enhancement, $s_b(n)$ and $y_b(n)$ are expressed in a state-space form as,

$$\begin{cases}
    s_b(n) = F s_b(n - 1) + G v_b(n) \\
    y_b(n) = H s_b(n) + w_b(n)
\end{cases}, \quad (5)$$

where $s_b(n) = [s_b(n - p + 1), \ldots, s_b(n)]^T$ denotes the speech state vector, $F$ is the transition matrix given by

$$F = \begin{bmatrix}
    0 & 1 & \cdots & 0 & 0 \\
    0 & 0 & \cdots & 0 & 0 \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    0 & 0 & \cdots & 0 & 1
\end{bmatrix},$$

and $H = G = [0, \ldots, 0, 1]^T \in \mathbb{R}^p$.

Given the corrupted subband speech $y_b(n)$, the Kalman filter recursively calculates an unbiased and linear MMSE estimate of the state vector $s_b(n)$. The denoising process can be summarized by the following recursive equations:

$$\begin{align*}
    e(n) &= y_b(n) - H^T \hat{s}_b(n|n-1) \\
    K(n) &= P(n|n-1) H (H^T P(n|n-1) H^T + \sigma^2_v)^{-1} \\
    \hat{s}_b(n|n) &= \hat{s}_b(n|n-1) + K(n) e(n) \\
    P(n|n) &= (I - K(n) H) P(n|n-1) \\
    \hat{s}_b(n+1|n) &= F \hat{s}_b(n|n) \\
    P(n+1|n) &= FP(n|n) F^T + \sigma^2_G \sigma^2_v G^T
\end{align*}, \quad (7)$$

where $\hat{s}_b(n|n-1)$ is a priori estimate of the current state vector $s_b(n)$; $P(n|n-1)$ the predicted state error correlation matrix of $\hat{s}_b(n|n-1)$, $e(n)$ the innovation, $K(n)$ the Kalman gain matrix, $\hat{s}_b(n|n)$ the filter estimate of state vector $s_b(n)$, and $P(n|n) = $ the filtered state error covariance matrix of $\hat{s}_b(n|n)$. The enhanced subband speech $\hat{s}_b(n)$ is finally given by

$$\hat{s}_b(n) = G^T \hat{s}_b(n|n).$$

(8)

To perform Kalman filtering, three parameters in Eq. (7) should be determined beforehand, that is, the additive noise variance $\sigma^2_v$, the driving noise variance $\sigma^2_v$, and the transition matrix $F$ with the LPCs of the clean subband speech. In our method, the additive noise variance is estimated and updated during the unvoiced frames and the driving noise variance is given by

$$\sigma^2_v = \sigma^2_v - \sigma^2_v,$$

where $\sigma^2_v$ can be computed from the noisy observation with Levinson-Durbin algorithm [17]. The estimation of the LPCs of $s_b(n)$ is introduced in the following subsection.

### 2.3. DNN based LSFs estimation

To begin with, the LPCs are converted to the LSFs in DNN based estimation since the well-behaved dynamic range of LSFs is suitable for a stable DNN training process [7, 10]. The DNN based LSFs estimation is divided into off-line and on-line
phases. In the off-line phase, a DNN is trained to learn the mapping between the acoustic features of noisy subband speeches and the LSFs of the clean counterparts. In the on-line phase, given the features of a noisy subband speech, the well-trained DNN predicts the LSFs of the clean subband speech. It should be mentioned that instead of training several DNNs for different subbands separately, we employ a single DNN for all the subband speeches to better exploit the relationships within different subbands as well as to reduce the computational and structural complexity.

For the input of DNN, we extract LSFs along with four acoustic features [18] of the noisy speech to represent the speech characteristics. The input features are extracted for each frame of the noisy speech. To make a full use of the temporal information of speech, we incorporate the features of the adjacent two frames into a single extended feature vector, which is then normalized for effective training.

The structure of the DNN used in our proposed system is shown in Fig.2. It is fully-connected and consists of one input layer, three hidden layers with 1024 units in each layer, and one output layer. The activation function used in the hidden layer is the rectified linear unit (ReLU), while a linear function is used in the output layer.

![Proposed DNN for LSFs estimation.](image)

Back propagation is used to find the optimal weights and biases of the DNN to minimize the cost function, which is defined as the mean square error (MSE) between the reference LSFs and the estimated ones for all subbands,

$$E_r = \frac{1}{J+1} \sum_{b=1}^{J+1} \left\{ \frac{1}{M_b} \sum_{m=1}^{M_b} \left\{ \frac{1}{p} \sum_{i=1}^{p} \left[ L_{b,i}(m) - L_{b,i}^{\hat{}}(m) \right]^2 \right\} \right\}$$

(10)

where $M_b$ denotes the total number of frames for the $b$-th noisy subband speech, $L_{b,i}(m)$ and $L_{b,i}^{\hat{}}(m)$ are the reference and the estimated LSFs for frame $m$, respectively, where $i \in \{1, ..., p\}$ is the order index of the clean speech AR model.

In summary, the proposed DNN assisted subband Kalman filtering system includes an off-line training phase and an online enhancement phase. The former trains a DNN with subband noisy and clean speech pairs, while the latter is described in detail below.

- Decompose the full-band noisy speech $y(n)$ into the subband versions $\{y_{b}(n)\}$ with DWT.
- Extract the features of each noisy subband speech and employ the trained DNN to obtain the estimated LSFs, which are converted to the LPCs to form the transition matrix $F$.
- Estimate the additive noise variance $\sigma_n^2$ during unvoiced frames and compute the driving noise variance $\sigma_v^2$ using Eq. (9).
- Perform Kalman filtering with Eq. (7) for each noisy subband speech $y_{b}(n)$ to obtain the enhanced counterpart $\hat{s}_{b}(n)$.
- Synthesize the enhanced subband speeches $\{\hat{s}_{b}(n)\}$ to reconstruct the final enhanced speech $\hat{s}(n)$ with IDWT.

3. Experimental results

3.1. Experimental setup

Clean speeches are selected from the IEEE sentence database [19], among them 670 utterances are used for the off-line training and 50 different utterances for the on-line enhancement. Eight types of noise from NOISEX-92 database [20] are picked to generate the noisy speeches, in which four types (babble, white, street, factory) are used as seen noise, and another four types (pink, buccaneer2, destroyerengine, hfchannel) as unseen noise. The mixing SNR levels are set to -3dB, 0dB, 3dB and 6dB. In the off-line phase, only seen noise is mixed with the training clean speech, which results in 10720 noisy and clean speech pairs. In the on-line phase, both seen and unseen noises are mixed with testing clean speech, giving 800 noisy speeches for both seen and unseen noise. The sampling frequency is set to 16 kHz for both clean speech and noise. It should be noted that since our proposed system aims to enhance the noisy subband speeches in the on-line phase, the noisy and clean speeches in off-line phase are also decomposed into their respective subband signals for the DNN training. A rectangular window is used to divide the audio signals into 20 ms frames with no overlap. For subband Kalman filtering, we set $s_0(0) = 0$, $P(0|0) = I$, and the AR model order as $p = 12$.

To evaluate the enhancement performance, two objective metrics are selected: the perceptual evaluation of speech quality (PESQ) measure [21] and the short-time objective intelligibility (STOI) measure [22]. PESQ and STOI evaluate the processed speech from speech quality and intelligibility perspectives, respectively. For both metrics, a higher score means a better speech quality or intelligibility.

3.2. Level of subband analysis

First, we decompose the noisy speech at different levels to find the optimal subband analysis level $J$ in our system. Three levels ($J = 1, 2, 3$) are tested under seen noise. Table 1 shows the objective results under the assumption that the clean speech is accessible to obtain ideal AR parameters for Kalman filtering. In this case, the three subband Kalman filters outperform the full-band processing, which indicates that denoising in each subband indeed removes the additive noise better and introduces less speech distortion. In addition, decomposing the speech with a deeper level contributes to a better performance when the ideal parameters are available.

Table 2 shows the objective results where the DNN-estimated AR parameters are employed for Kalman filtering. We find that adopting 1-level DWT for subband analysis, namely, decomposing the noisy speech into two subband speeches, leads to the best result. As the subband analysis level gets deeper, the number of the input subband signals is increased, which requires a more complex structure to perfectly learn the relationships between more input features and the targets. As such, the 1-level led to better enhancement result. Another possible reason is that if we decompose at a deeper level,
more Kalman filters are required. Since the parameters cannot be ideally estimated for each Kalman filter, the estimation error leads to a degradation of the enhanced subband speeches. Thus, the synthesized full-band speech suffers more performance decrease for high-level subband analysis cases. As a result, we choose 1-level decomposition in our system.

Table 1: **Objective results using ideal AR parameters for Kalman filtering under seen noise**

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<th>-3dB</th>
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<tbody>
<tr>
<td><strong>PESQ</strong></td>
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<tr>
<td>Noisy</td>
<td>1.41</td>
<td>1.52</td>
<td>1.68</td>
<td>1.86</td>
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<tr>
<td>Full-band processing</td>
<td>2.37</td>
<td>2.54</td>
<td>2.70</td>
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<tr>
<td>1-level analysis</td>
<td>2.38</td>
<td>2.55</td>
<td>2.72</td>
<td>2.90</td>
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<tr>
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<td>0.88</td>
<td>0.90</td>
<td>0.92</td>
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Table 2: **Objective results using estimated AR parameters for Kalman filtering under seen noise**

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<td>0.69</td>
<td>0.75</td>
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### 3.3. Performance evaluation

Four existing algorithms are adopted as reference methods to compare with our proposed system (DNN-SKF). They are the iterative Kalman filter (I-KF) [2], the perceptual Kalman filter (P-KF) [3], the DNN assisted Kalman filter (DNN-KF) [10] and the DNN based complex ideal ratio masking method (DNN-CIRM) [9]. Since the traditional Kalman filters do not involve a training stage for parameter estimation, experiments are conducted on unseen noise only for fair comparison.

Table 3 shows the average objective scores of different Kalman filter based algorithms. Obviously, DNN-KF and our DNN-SKF outperform the other two traditional unsupervised Kalman filter based algorithms, which indicates that the employment of DNN can provide more accurate LPCs estimates, and thus improve the enhancement performance of Kalman filtering. Moreover, our DNN-SKF has better objective scores than DNN-KF in most cases. It can be inferred that the subband Kalman filtering still works even on unseen noise. Comparing the results of DNN-SKF in Table 3 with that in Table 2 (the 1-level analysis case under seen noise), the performance under unseen noise does not decrease notably, which demonstrates a good generalization capability of our DNN-SKF. Comparing DNN-SKF with DNN-CIRM, DNN-SKF achieves better perceptual quality, while DNN-CIRM gives a better score of objective speech intelligibility.

Table 3: **Objective results of different enhancement methods under unseen noise**

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<tr>
<td>Noisy</td>
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<td>1.51</td>
<td>1.65</td>
<td>1.82</td>
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<tr>
<td>I-KF</td>
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<td><strong>STOI</strong></td>
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![Figure 3: Spectrograms of clean, noisy and enhanced speeches.](image)

### 4. Conclusions

In this paper, a DNN assisted subband Kalman filtering system has been proposed for speech enhancement, which first decomposes the noisy speech into subbands and then performs Kalman filtering in each subband. A DNN has been introduced for LSFs estimation in order to provide more accurate LPCs for Kalman filtering. Experiments have shown that our system outperforms several existing Kalman filter based algorithms. There are two possible reasons behind this improvement. Firstly, the powerful learning ability of DNN helps to estimate LPCs with high accuracy. Secondly, the subband Kalman filtering reduces the speech distortion and efficiently removes the background noise with respect to different frequencies.
5. References


