Modulation-Domain Kalman Filtering for Monaural Blind Speech Denoising and Dereverberation

Nikolaos Dionelis, Mike Brookes, Member, IEEE

Abstract—We describe a monaural speech enhancement algorithm based on modulation-domain Kalman filtering to blindly track the time-frequency log-magnitude spectra of speech and reverberation. We propose an adaptive algorithm that performs blind joint denoising and dereverberation, while accounting for the inter-frame speech dynamics, by estimating the posterior distribution of the speech log-magnitude spectrum given the log-magnitude spectrum of the noisy reverberant speech. The Kalman filter update step models the non-linear relations between the speech, noise and reverberation log-spectra. The Kalman filtering algorithm uses a signal model that takes into account the reverberation parameters of the reverberation time, T_{60} , and the direct-to-reverberant energy ratio (DRR) and also estimates and tracks the T_{60} and the DRR in every frequency bin to improve the estimation of the speech log-spectrum. The proposed algorithm is evaluated in terms of speech quality, speech intelligibility and dereverberation performance for a range of reverberation parameters and reverberant speech to noise ratios, in different noises, and is also compared to competing denoising and dereverberation techniques. Experimental results using noisy reverberant speech demonstrate the effectiveness of the enhancement algorithm.

Index Terms—Speech enhancement, dereverberation, Kalman filtering, minimum mean-square error (MMSE) estimation.

I. INTRODUCTION

NOWADAYS, technology is ever evolving with tremendous haste and the demand for speech enhancement systems is evident. Speech enhancement in noisy reverberant environments, for human listeners, is challenging. Speech is degraded by noise and reverberation when captured using a near-field or far-field distant microphone [1] [2]. A room impulse response (RIR) can include components at long delays, hence resulting in reverberation and echoes [3] [4]. Reverberation is a convolutive distortion, induces long-term correlation between consecutive observations and can be quite long with a reverberation time, T_{60} , of more than 0.8 s. Reverberation and noise, which can be stationary or non-stationary, have a detrimental impact on both speech quality and speech intelligibility.

The direct to reverberant energy ratio (DRR) and the reverberation time, T_{60} , are the two main parameters of a reverberation model [5] [1]. The DRR describes reverberation in the space domain, depending on the positions of the source and the receiver. The T_{60} is the time interval required for a sound level to decay 60 dB after ceasing its original stimulus. The T_{60} , when measured in the diffuse sound field, depends on the room and is independent of the source to microphone configuration. The impact of reverberation on perception depends on the T_{60} . If the T_{60} is short, the environment reinforces the sound which

may enhance the sound perception [6] [7]. If the T_{60} is long, then spoken syllables interfere with future ones. Reverberation spreads energy over time and because of this smearing across time, (a) the energy of individual phones spreads out in time, (b) plosives have a delayed decay and fricatives are smoothed, and (c) preceding phones blur into the current phones.

The aim of speech enhancement is to reduce and ideally eliminate the effects of both noise and reverberation without distorting the speech signal [8]. Enhancement algorithms typically aim to suppress noise and late reverberation because early reverberation is not perceived as separate sound sources and usually improves speech quality and intelligibility. Noise is assumed to be uncorrelated with speech, early reverberation is correlated with speech and late reverberation is commonly assumed to be uncorrelated with speech, as in [6] and [9].

Speech enhancement can be performed in different domains. The ideal domain should be chosen such that (a) good models of speech and noise exist in this domain, and (b) speech and noise are separable in this domain. Speech and noise are additive in the Short Time Fourier Transform (STFT) domain [10] [11]. The relation between speech and noise becomes progressively more complicated in the amplitude, power and log-power spectral domains. Noise suppression algorithms operate in a time-frequency domain and these techniques have been extended to address dereverberation. In [9], spectral enhancement methods based on a time-frequency gain, originally developed for noise suppression, have been modified and employed for dereverberation. Such algorithms suppress late reverberation assuming that the early and late reverberation components are uncorrelated. The spectral enhancement methods in [12] [9] estimate the late reverberant spectral variance (LRSV) and use it in the place of the noise spectral variance, reducing the problem of late reverberation suppression to that of estimating the LRSV [6]. In [7], blind spectral weighting is employed to reduce the overlap-masking effect of reverberation using an uncorrelated additive assumption for late reverberation.

Dereverberation methods that leave the phase unaltered and operate in the amplitude, power or log-power spectral domains are relatively insensitive to minor variations in the spatial placement of sources [13]. Two criticisms of spectral enhancement algorithms based on LRSV reverberation noise estimation are that they introduce musical noise and suppress speech onsets when they over-estimate reverberation [14]. The LRSV estimator in [15], which is an extension of [6], models the RIR in the STFT domain and not in the time domain [16], using the RIR model from Polack [17] or Moorer [18] [16]. Reverberation is estimated in [15] using the energy of the direct path of the speech and an external T_{60} estimate.

Modelling the temporal dynamics of speech is beneficial

N. Dionelis and M. Brookes are with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, U.K. (e-mail: nikolaos.dionelis11@imperial.ac.uk; mike.brookes@imperial.ac.uk).

when the T_{60} is long and the DRR is low [19] [2]. Blind joint denoising and dereverberation using speech and noise tracking is performed in [19]. The SPENDRED algorithm [20] [21], which is a model-based method with a convolution model for reverberation based on the T_{60} and the DRR, considers the speech temporal dynamics. SPENDRED employs a parametric model of the RIR [22] and performs frequency-dependent and time-varying T_{60} and DRR estimation. However, unless the source or the microphone are moving, the T_{60} and the DRR will be constant throughout the recording. The SPENDRED algorithm assumes that $DRR \geq 1 - (10^{-6})^{\frac{L}{T_{60}}}$ where L is the acoustic frame increment. For example, when $T_{60} = 0.4$ s and $L = 5$ ms, then $DRR \geq -8$ dB is assumed. In addition, SPENDRED performs intra-frame correlation modelling, which can be beneficial in adverse conditions, while typical algorithms decouple different frequency bands, as in [10].

Statistical-based methods, such as SPENDRED, model reverberation as a convolution in the power spectral domain while LRSV methods treat reverberation as an additive distortion in the power spectral domain [22] [23]. A model with an infinite impulse response is used either with the two parameters of the T_{60} and the DRR, as in [20] [21], or with a larger number of parameters. The low-order convolution model of reverberation with the T_{60} and the DRR is parsimonious [20] [21] and contrasts with the higher-order autoregressive processes in the complex STFT domain used in [24] [25].

The algorithms described in [26], [22] and [23] create non-linear observation models of noisy reverberant speech in the log Mel-power spectral domain, using the reverberation-to-noise ratio (RNR). As discussed in [27], phase differences in Mel-frequency bands have different properties from phase differences in STFT bins. The phase factor between reverberant speech and noise is different from that between speech and noise and is examined in [22] for Mel-frequency bands.

In noisy reverberant conditions, identifying speech onsets and determining which frames are unvoiced/silence is difficult, due to the smearing across time that leads to noise over-estimation. The concatenation of different techniques for denoising and dereverberation was found in [19] to have lower performance than unified methods due to over-estimating noise when estimating noise and reverberation separately. Nevertheless, long-term linear prediction with pre-denoising can be used to suppress noise and reverberation. In the weighted prediction error (WPE) algorithm [28] [2], reverberation is modelled by a one-dimensional convolution in each frequency bin. In [29], the WPE method is discussed along with inter-frame correlation. In [30], the WPE method is used in the complex STFT domain performing batch processing and iteratively estimating, first, the reverberation prediction coefficients and then, the speech spectral variance. In [31] [32], WPE linear filtering is employed in the STFT power spectral domain.

In recent years, much effort has been devoted to developing speech enhancement and dereverberation algorithms that use deep learning (DL) approaches to estimate either the STFT amplitudes directly or, more commonly, a real or complex valued gain mask in the STFT domain [33]. These DL approaches, such as the ones presented in [34], [35] and [36], have consistently been shown to give enhancement

performance that is better than conventional model-based enhancement, such as the Log-MMSE enhancer [37], especially in highly non-stationary noise. Data-driven methods have also been applied successfully to removing both noise and reverberation either jointly, in [38] and [39], or sequentially, in [40] and [41]. Dereverberation based on supervised learning using ratio or binary masking [42], considering the early and late reverberant speech components, is examined in [43]. A concern with DL approaches to enhancement and dereverberation has been a lack of robustness to mismatches between the type of noise in training and testing. It has been observed that speech enhancement performance declines in mismatched conditions [44] and a number of researchers have tried to improve robustness by including model-based features as additional inputs [45] [46]. In DL approaches, there is also an important computational aspect to be considered. Each language and combination of environmental factors requires a separate round of training resulting in an exponential complexity burden.

The use of a time-domain Kalman filter (KF) for speech enhancement was first suggested by [47]. This was extended by [48] who proposed tracking both speech and noise and proposed two alternative methods of estimating time-dependent AR models for the speech and noise. However, it was found that neither method outperformed the Log-MMSE enhancer [37]. In [49], a KF enhancer was combined with a perceptual post-filter based on the masking properties of the human ear. In [50] [51], a modulation-domain speech enhancer was proposed that used a KF to estimate the clean speech spectral amplitudes using a linear KF update step and this was found to outperform the time-domain KF of [47]. This approach was extended in [10] to use an improved signal model in which speech and noise were additive in the complex STFT domain rather than in the spectral amplitude domain. This was further developed in [52] to minimise the squared error in the log-spectral domain and to track the speech phase in addition to the speech and noise amplitudes. Non-linear KFs that take into account that speech and noise add in the STFT domain are formulated in [53], [54] and [11]. A modulation domain KF proposed in [55] used a complex AR model of order 20, which corresponds to 320 ms, for dereverberation. It used a similar approach to that of [48] to estimate both the speech spectral values and the AR coefficients online. In contrast to traditional KFs that are linear, do not model reverberation and are implemented in the time domain [47], the proposed algorithm is non-linear, performs blind speech dereverberation and models reverberation as an autoregressive process in the prediction step and as a phase-sensitive process in the update step. In this paper, phase-sensitive modulation-domain Kalman filtering for speech enhancement [56], joint noise suppression and dereverberation, is performed in an adaptive manner.

This paper presents an adaptive denoising and dereverberation Kalman filtering framework that tracks the speech and reverberation spectral log-magnitudes. In this paper, we extend the enhancer in [53] to include dereverberation, taking into account inter-frame correlations. We use an integrated structure of two parallel signal models to track speech, reverberation and the T_{60} and DRR reverberation parameters. The T_{60} and the DRR are updated in every frame to improve the estimation

of the speech log-spectrum. We create an observation model and a series of non-linear KF update steps that perform joint noise and reverberation suppression by estimating the first two moments of the posterior of the speech log-spectrum given the noisy reverberant log-spectrum. In contrast to [50] and [10], the log-spectral domain is chosen for the KF state, as in [52] and [53], because speech log-spectra are well modelled by Gaussian distributions and the mean squared error (MSE) in the log-spectral domain is a good measure to use for perceptual quality [57] [58]. Modelling spectral log-amplitudes as Gaussian distributions leads to good speech modelling in noisy reverberant environments because super-Gaussian distributions can model the speech amplitude spectrum well [11] [54].

The structure of this paper is as follows. Section II describes the signal model and Sec. III presents the enhancement algorithm and its non-linear KF. The implementation and the validation of the algorithm are in Sec. IV. The algorithm's evaluation is in Sec. V. Conclusions are drawn in Sec. VI.

II. SIGNAL MODEL AND NOTATION

In the complex STFT domain, the noisy speech, $Y_t(k)$, is given by $Y_t(k) = S_t(k) + R_t(k) + N_t(k)$ where $S_t(k)$ is the direct speech component, $R_t(k)$ is the reverberant speech component and $N_t(k)$ is the noise, as for example in [24] [25]. The time-frame index is t and the frequency bin index is k . For convenience, we define $Z_t(k) = R_t(k) + N_t(k)$. We drop the time and frequency indexes and we obtain $Y = S + Z = S + R + N$. We define the log-magnitude spectrum of S as $s = \log(|S|)$ and we also define r , n , y and z similarly.

The algorithm treats each frequency bin on its own. Within the algorithm, t is included as a subscript in equations involving multiple frames. Signal quantities with capital letters, such as S_t , are complex numbers with magnitude and phase, $|S_t|$ and $\angle S_t$. The reverberation power, $|R_t|^2$, in frame t consists of two components: (a) the decaying reverberation that was present in the previous frame with power $a_t|R_{t-1}|^2$, and (b) a new reverberation component arising from the speech signal in the previous frame with power $b_t|S_{t-1}|^2$. Here, $a_t, b_t \in \mathbb{R}$ respectively model the decay rate of the old reverberation component and the scale factor of the new reverberation component. The reverberation signal model is given by

$$\begin{aligned} R_t &= \sqrt{a_t} R_{t-1} \exp(j\theta_t) + \sqrt{b_t} S_{t-1} \exp(j\psi_t) \\ &= \sum_{\tau=1}^{\infty} \left(\prod_{i=1}^{\tau-1} (\sqrt{a_{t-i+1}} \exp(j\theta_{t-i+1})) \right) \\ &\quad \times \sqrt{b_{t-\tau+1}} S_{t-\tau} \exp(j\psi_{t-\tau+1}). \end{aligned} \quad (1)$$

If both a_t and b_t are time-invariant and S_t is a unit impulse at $t = 0$, then (1) reduces to $|R_t|^2 = b_t a_t^{t-1}$ with a total reverberation power of $\sum_{t=1}^{\infty} |R_t|^2 = \frac{b_t}{1-a_t}$ from which

$$a_t^{\frac{T_{60}}{L}} = 10^{-6}, \quad b_t = \frac{1-a_t}{\text{DRR}} \quad (2)$$

where L is the acoustic frame increment in seconds. In (1), the factors $\exp(j\theta_t)$ and $\exp(j\psi_t)$, where θ_t and ψ_t are assumed to be uniformly distributed phases, denote the phases of the old and new reverberation components, respectively. In (2),

Table I
List of the main variables in the log-magnitude spectral domain.

Variable	Equation	Description
n_t	$\log(N_t)$	Noise signal
r_t	$\log(R_t)$	Reverberation signal
s_t	$\log(S_t)$	Speech signal
y_t	$\log(Y_t)$	Noisy reverberant speech signal
z_t	$\log(Z_t)$	Reverberation plus noise signal
β_t	(5)	Reverberation scale factor
γ_t	(4)	Reverberation decay factor
δ_t	(4)	Old reverberation component
ϵ_t	(5)	New reverberation component

Figure 1. Plot of β , using $L = 8$ ms in (2), against: (a) T_{60} when the DRR is 4, 0 and -4 dB, and (b) DRR when the T_{60} is 0.2, 0.5 and 0.8 s.

the DRR is defined in the power spectral domain [20] [21]. The T_{60} and the DRR depend on time and frequency [5].

Equation (1) is the convolution model for reverberation; the most common reverberation model is this single-pole filter described by the pole and zero positions that depend on the T_{60} and the DRR [20] [2]. A convolution of infinite order is used in (1) to describe reverberation [20] [21], and models that describe reverberation by a convolution are also discussed in [22] [23]. The signal model is defined by (1) and by

$$Y_t = S_t + Z_t, \quad Z_t = R_t + N_t, \quad (3)$$

$$\gamma_t = 0.5 \log(a_t), \quad \delta_t = \gamma_t + r_{t-1} = \log(\sqrt{a_t} |R_{t-1}|), \quad (4)$$

$$\beta_t = 0.5 \log(b_t), \quad \epsilon_t = \beta_t + s_{t-1} = \log(\sqrt{b_t} |S_{t-1}|) \quad (5)$$

where $b_t > 0$, $0 < a_t < 1$ and $\gamma_t < 0$. A list of variables in the log-magnitude spectral domain is shown in Table I.

Figure 1 shows graphs of β against T_{60} for a fixed DRR and of β against DRR for a fixed T_{60} . If DRR = 0 dB, then $b_t = 1 - a_t$. If $\beta_t = 0$, then $b_t = 1$ and DRR = $1 - a_t$.

Figure 2 depicts the flowchart of the signal model. Equations (1) and (3), together with Fig. 2, define the high-level signal decomposition. The reverberation signal model in (1) uses $\sqrt{a_t}$ and $\sqrt{b_t}$ because the a_t and b_t reverberation parameters, in (2), are defined in the power spectral domain [20] [21]. The a_t and b_t parameters are mapped to γ_t and β_t using (4) and (5). The signals z_t , δ_t and ϵ_t are the total disturbance, the old (decaying) reverberation and the new reverberation, respectively. In this case, z_t is defined in Table I and δ_t and ϵ_t in (4) and (5).

The signal model of how the reverberation parameters of γ_t and β_t change over time is a random walk model. This is used in the algorithm's KF prediction step for γ_t and β_t .

The signal model in Fig. 2 is linked to the alternating and interacting KFs of the algorithm. The algorithm is a collection

Figure 2. The flowchart diagram of the proposed signal model of the speech enhancement algorithm. The KF's signal model is given by (1) and (3).

of two KFs, the speech KF and the reverberation KF, that estimate the speech and reverberation log-spectra and the γ_t and β_t reverberation parameters, as described in Sec. III.

III. THE SPEECH ENHANCEMENT ALGORITHM

The adaptive KF algorithm operates in the log-magnitude spectral domain and Fig. 3 depicts the denoising and dereverberation algorithm that formulates a model of reverberation as a first-order autoregressive process. The algorithm propagates the means and variances of the random variables. Almost all the signals are assumed to follow a Gaussian distribution and the distribution of s_t conditioned on observations up to time τ is denoted by $p_{s_t|\tau}(s) \triangleq p(s_t|y_0, \dots, y_\tau) = N(s_t|\tau, \Sigma_{t|\tau}^{(s)})$. A Gaussian distribution is denoted by its mean, $s_{t|\tau}$.

The core of the algorithm in Fig. 3 is the KF that comprises gray blocks in the flowchart diagram. The non-linear KF estimates and tracks the posterior distributions of the speech log-magnitude spectrum, s_t , the reverberation log-magnitude spectrum, r_t , and the reverberation parameters, γ_t and β_t .

The input to the algorithm in Fig. 3 is the noisy reverberant speech in the time domain. The algorithm's first step is to obtain the signal in the complex STFT domain. The algorithm does not alter the noisy reverberant phase, $\angle Y$, and uses the noisy reverberant amplitude spectrum, $|Y|$, in three ways: in the speech KF prediction step, in the KF update step and in the noise power modelling. The speech KF state, $\mathbf{s}_t \in \mathbb{R}^p$, is the speech log-spectrum from the previous p frames [52],

$$\mathbf{s}_t = (s_t \ s_{t-1} \ \dots \ s_{t-p+1})^T. \quad (6)$$

The linear speech KF prediction step is based on autoregressive (AR) modelling on the log-spectrum of pre-cleaned speech. The reverberation KF state is r_t and the KF states of the reverberation parameters are γ_t and β_t . The KF observation is the noisy reverberant speech log-spectrum, y_t , which is used in the KF update step to compute the first two moments of the posterior of the speech log-spectrum. The mean of the speech log-spectrum posterior is used together with $\angle Y$ to create the enhanced speech signal using the inverse STFT (ISTFT).

Apart from the speech log-spectrum, the non-linear KF also tracks the reverberation log-spectrum, r_t , and the γ_t and β_t reverberation parameters. Hence, the KF state is of dimension $(p+3)$ and may be partitioned as $(\mathbf{s}_t^T \ r_t \ \gamma_t \ \beta_t)^T$. The KF, as defined by the gray blocks in Fig. 3, has a speech KF prediction step, a reverberation KF prediction step and a series of KF update steps. The reverberation KF is comprised of the blocks "Reverberation KF prediction", "KF Update" and " γ_t , β_t KF Update". These three blocks perform joint denoising and dereverberation and also estimate both $s_{t|t}$ and $\Sigma_{t|t}^{(s)}$.

The structure of this section is as follows. Sections III.A and III.B present the speech and reverberation prediction steps, respectively. Sections III.C and III.D describe the update step and Sec. III.E the priors for the γ_t and β_t parameters that are needed so that the KF (a) distinguishes between s_t and r_t , and (b) does not diverge to non-realistic γ_t and β_t estimates. Finally, Sec. III.F presents the unshaded blocks in Fig. 3.

A. The Speech KF Prediction Step

The purpose of the speech KF prediction step is to predict the prior of the state vector, $s_{t|t-1}$, from the previous frames posterior distribution, $s_{t-1|t-1}$, [52]. The AR modelling and the KF prediction step correlate the current frame element of the speech state vector, $\mathbf{s}_t$, with the previous $(p-1)$ frame elements of $\mathbf{s}_t$ [53]. For $\mathbf{s}_t$, the speech signal model is

$$\mathbf{s}_{t|t-1} = \mathbf{A}_t^{(s)} (\mathbf{s}_{t-1|t-1} - \zeta_t^{(s)} \mathbf{1}_p) + \zeta_t^{(s)} \mathbf{1}_p + \mathbf{w}_t^{(s)} \quad (7)$$

where $\mathbf{1}_p$ denotes the unity vector, $\mathbf{1}_p \in \mathbb{R}^p$. In (7), $\zeta_t^{(s)} \in \mathbb{R}$ is the AR mean [52], $\mathbf{w}_t^{(s)} \in \mathbb{R}^p$ with only its first element being non-zero is zero-mean with covariance matrix $\mathbf{Q}_t^{(s)}$, and

$$\mathbf{A}_t^{(s)} = \begin{pmatrix} -\mathbf{a}_t^{(s)T} \\ \mathbf{I}_{(p-1)} \end{pmatrix} \in \mathbb{R}^{p \times p}, \quad (8)$$

$$\mathbf{Q}_t^{(s)} = \mathbb{E}\{\mathbf{w}_t^{(s)} \mathbf{w}_t^{(s)T}\} = \begin{pmatrix} \epsilon_t^{(s)} & \mathbf{0}_{(p-1) \times 1}^T \\ \mathbf{0}_{(p-1) \times 1} & \mathbf{0}_{(p-1) \times (p-1)} \end{pmatrix} \quad (9)$$

where $\mathbf{I}_p \in \mathbb{R}^{p \times p}$ denotes the identity matrix and $\mathbf{0}_{p \times p} \in \mathbb{R}^{p \times p}$ the zero matrix. The KF transition matrix is $\mathbf{A}_t^{(s)}$, the KF transition noise covariance matrix is $\mathbf{Q}_t^{(s)}$ and the KF transition noise is $\mathbf{w}_t^{(s)}$. The AR coefficients vector is $\mathbf{a}_t^{(s)} \in \mathbb{R}^p$ and the variance of the transition noise is $\epsilon_t^{(s)}$. In (7), $\mathbf{A}_t^{(s)}$, $\zeta_t^{(s)}$ and $\mathbf{Q}_t^{(s)}$ are estimated from AR modeling of order p , i.e. AR(p) modeling. The AR mean, $\zeta_t^{(s)}$, is the mean speech spectral log-amplitude estimated as an AR parameter, as in [52].

The KF prediction step, which uses conditional distributions to model short-term dependencies [52] [53], comprises the blocks: "Speech KF prediction", "Decorrelate" and "Recorrelate". Decorrelation and recorrelation of $\mathbf{s}_t$ are performed after and before the KF prediction, respectively. Decorrelation and recorrelation are performed so that the non-linear update step can be applied and perform vector-matrix and matrix-matrix multiplications for the speech KF state mean and its covariance matrix, respectively, using $\mathbf{B}_t \in \mathbb{R}^{p \times p}$ [54]. The outputs of the "Decorrelate" block are s_t and the rest elements of $\mathbf{s}_t$.

The prediction step propagates the first two moments of the state [52] [58] and predicts $\mathbf{s}_t$ as the linear transformation of $\mathbf{s}_{t-1}$ given in (7) using the AR coefficients obtained from the "Speech AR(p)" block in Fig. 3, which has pre-cleaned speech as an input. After the prediction step, $\mathbf{s}_t$ is correlated so in order to simplify the KF update and impose the observation constraint [10], we apply a linear transformation matrix, $\mathbf{B}_t$. We decorrelate $\mathbf{s}_t$ with a linear transformation and $\mathbf{B}_t$ is chosen to decorrelate the current frame element, s_t , from the rest of the state vector so that the algorithm performs the update step with the variable in the current frame [54]. After the KF update step, recorrelation is applied with a linear transformation, using $\mathbf{B}_t^{-1}$, to continue the KF recursion and to preserve the inter-frame correlation created from the prediction step.

Figure 3. The flowchart of the algorithm to suppress noise and reverberation. For clarity, the signal variances are not included. The gray blocks constitute the KF that tracks the speech and reverberation log-spectra and the reverberation parameters. The “KF Update” and “ γ_t, β_t KF Update” blocks constitute the non-linear KF update step that uses the signal model described in Sec. II.

A bar diacritic, $\bar{\cdot}$, is used to indicate the transformed domain, $\bar{\mathbf{s}} = \mathbf{B}\mathbf{s}$. The posteriors, $\bar{\mathbf{s}}_{t|t}$ and $\bar{\Sigma}_{t|t}^{(s)}$, are computed in the KF update step in this domain. First, $\Sigma_{t|t-1}^{(s)}$ is partitioned as

$$\Sigma_{t|t-1}^{(s)} = \begin{pmatrix} \Sigma_{t|t-1}^{(s)} & \mathbf{p}_{B,t|t-1}^T \\ \mathbf{p}_{B,t|t-1} & \mathbf{P}_{C,t|t-1} \end{pmatrix} \quad (10)$$

where a sufficient condition for $\Sigma_{t|t-1}^{(s)}$ to be non-zero is that $\epsilon_t^{(s)}$ in (9) is non-zero. For decorrelation, $\mathbf{B}_t$ is given by

$$\mathbf{B}_t = \begin{pmatrix} 1 & \mathbf{0}_{1 \times (p-1)} \\ -(\Sigma_{t|t-1}^{(s)})^{-1} \mathbf{p}_{B,t|t-1} & \mathbf{I}_{(p-1)} \end{pmatrix}. \quad (11)$$

The transformed mean and covariance matrix are given by

$$\bar{\mathbf{s}}_{t|t-1} = \mathbf{B}_t \mathbf{s}_{t|t-1} = \begin{pmatrix} s_{t|t-1} & \bar{\mathbf{s}}_{C,t|t-1}^T \end{pmatrix}^T, \quad (12)$$

$$\bar{\Sigma}_{t|t-1}^{(s)} = \mathbf{B}_t \Sigma_{t|t-1}^{(s)} \mathbf{B}_t^T = \begin{pmatrix} \Sigma_{t|t-1}^{(s)} & \mathbf{0}_{1 \times (p-1)} \\ \mathbf{0}_{(p-1) \times 1} & \mathbf{P}_{C,t|t-1} \end{pmatrix} \quad (13)$$

$$\bar{\mathbf{P}}_{C,t|t-1} = \mathbf{P}_{C,t|t-1} - (\Sigma_{t|t-1}^{(s)})^{-1} \mathbf{p}_{B,t|t-1} \mathbf{p}_{B,t|t-1}^T \quad (14)$$

where $\Sigma_{t|t-1}^{(s)}$ is preserved as the leading element in (13) and $\bar{\mathbf{s}}_{C,t|t-1} \in \mathbb{R}^{(p-1)}$ contains the elements that will not be changed by the non-linear update step in Sec. III.C. After the update step, the inverse transformation is applied with

$$\mathbf{s}_{t|t} = \mathbf{B}_t^{-1} \bar{\mathbf{s}}_{t|t}, \quad \Sigma_{t|t}^{(s)} = \mathbf{B}_t^{-1} \bar{\Sigma}_{t|t}^{(s)} \mathbf{B}_t^{-T}. \quad (15)$$

The posteriors $\bar{\mathbf{s}}_{t|t}$ and $\bar{\Sigma}_{t|t}^{(s)}$ are found and $\bar{\mathbf{s}}_{t|t}$ is given by

$$\bar{\mathbf{s}}_{t|t} = \begin{pmatrix} s_{t|t} & \bar{\mathbf{s}}_{C,t|t}^T \end{pmatrix}^T \quad \text{where} \quad \bar{\mathbf{s}}_{C,t|t} = \bar{\mathbf{s}}_{C,t|t-1}. \quad (16)$$

Using $\bar{\mathbf{P}}_{C,t|t} = \bar{\mathbf{P}}_{C,t|t-1}$, the posterior covariance matrix, $\bar{\Sigma}_{t|t}^{(s)}$, is obtained by replacing $\Sigma_{t|t-1}^{(s)}$ in (13) by $\Sigma_{t|t}^{(s)}$. Hence,

$$\bar{\Sigma}_{t|t}^{(s)} = \begin{pmatrix} \Sigma_{t|t}^{(s)} & \mathbf{0}_{1 \times (p-1)} \\ \mathbf{0}_{(p-1) \times 1} & \mathbf{P}_{C,t|t} \end{pmatrix} \quad (17)$$

$$\Sigma_{t|t}^{(s)} = \mathbb{E} \{s_t^2 | \mathcal{Y}_t\} - (\mathbb{E} \{s_t | \mathcal{Y}_t\})^2 \quad (18)$$

where $\mathcal{Y}_t = \{y_0, y_1, \dots, y_t\}$. In the update step in Sec. III.C, $\mathbb{E} \{s_t | \mathcal{Y}_t\}$ and $\mathbb{E} \{s_t^2 | \mathcal{Y}_t\}$ are computed. This formulation allows the use of non-Gaussian priors and is equivalent to the conventional KF if the state is assumed Gaussian [10].

B. The Reverberation KF Prediction Step

The algorithm uses a random-walk KF prediction step for γ_t and β_t that assumes that their means are preserved and their variances increase. A random-walk prediction step was used in [24]. The KF prediction step for γ_t and β_t is given by

$$\gamma'_{t|t-1} = \gamma_{t-1|t-1}, \quad \Sigma_{t|t-1}^{(\gamma')} = \Sigma_{t-1|t-1}^{(\gamma)} + Q_\gamma, \quad (19)$$

$$\beta'_{t|t-1} = \beta_{t-1|t-1}, \quad \Sigma_{t|t-1}^{(\beta')} = \Sigma_{t-1|t-1}^{(\beta)} + Q_\beta \quad (20)$$

in which Q_γ and Q_β are fixed variance increments for γ_t and β_t whose values depend on the expected rate of change of the T_{60} and DRR parameters, as discussed in Sec. IV. The variances of the reverberation parameter distributions will always increase in the KF prediction step but will normally then decrease in the update step described in Sec. III.C.

After the reverberation KF prediction step, the algorithm computes and imposes priors on γ_t and β_t using Gaussian-Gaussian multiplication. These internally computed priors in the “ γ_t, β_t priors” block in Fig. 3 are described in Sec. III.E. A prime diacritic, $\prime$, is used in (19) and (20) to denote the signals before the priors are imposed. After imposing the priors in Sec. III.E, we obtain $\gamma_{t|t-1}$, $\Sigma_{t|t-1}^{(\gamma)}$ and $\beta_{t|t-1}$, $\Sigma_{t|t-1}^{(\beta)}$.

The “Reverberation KF prediction” block estimates the first two moments of the prior distribution of the reverberation spectral log-amplitude, i.e. $r_{t|t-1}$ and its variance. The algorithm performs a reverberation KF prediction step based on the previous posterior of both speech and reverberation using the signal model in (1), where a is less than unity and this ensures that the reverberation KF prediction step is stable.

From (1) and Fig. 2, the STFT-domain reverberation is the sum of two components arising, respectively, from the reverberation and speech components of the previous frame. The old reverberation, δ_t , and the new reverberation, ϵ_t , are defined in (4) and (5), respectively. The algorithm calculates the prior distributions of these components in the log-spectral domain using $\delta_{t|t-1} = \gamma_{t|t-1} + r_{t-1|t-1}$ and $\epsilon_{t|t-1} = \beta_{t|t-1} + s_{t-1|t-1}$. These two equations are based on (4) and (5) with a common condition added to all terms. Assuming that r_{t-1} and s_{t-1} are uncorrelated with γ_t and β_t , respectively, the variances of the two Gaussian distributions add, in each case, to give

$$\Sigma_{t|t-1}^{(\delta)} = \Sigma_{t|t-1}^{(\gamma)} + \Sigma_{t-1|t-1}^{(r)}, \quad (21)$$

$$\Sigma_{t|t-1}^{(\epsilon)} = \Sigma_{t|t-1}^{(\beta)} + \Sigma_{t-1|t-1}^{(s)}. \quad (22)$$

The “Reverberation KF prediction” block in Fig. 3 computes $r_{t|t-1}$. The reverberation log-amplitude spectrum is estimated by modelling the addition in the complex STFT domain of two random variables in the log-amplitude spectral domain. Given two disturbance sources, i.e. δ_t and ϵ_t , the blind KF algorithm combines them into a single disturbance source, i.e. r_t .

For the remainder of Sec. III.B, the time subscript, $t|t-1$, is omitted for clarity. For example, $p(\delta)$ is used instead of $p_{\delta_{t|t-1}}(\delta)$ to denote the probability distribution of $\delta_{t|t-1}$.

From (1), the reverberation component is the STFT-domain sum of two elements arising, respectively, from the reverberation and speech components in the previous frame. The log-amplitude spectral domain distributions of these two elements, $\delta_{t|t-1}$ and $\epsilon_{t|t-1}$, were calculated in the preceding paragraphs. A two-dimensional Gaussian distribution is used for $p(\delta, \epsilon) = p(\delta)p(\epsilon)$ assuming independence between δ and ϵ . We assume that the phase difference, $\eta = \theta - \psi$, between the two disturbance sources in (1) is uniformly distributed, i.e. $\eta \sim U(-\pi, \pi)$, and independent of their magnitudes. Multiplying (1) by its complex conjugate, taking logs and applying (4) and (5) leads to $e^{2r} = e^{2\delta} + e^{2\epsilon} + 2\cos(\eta)e^{\delta+\epsilon}$ from which $r = 0.5 \log(e^{2\delta} + e^{2\epsilon} + 2\cos(\eta)e^{\delta+\epsilon})$ that depends on η , as in [52], [53] and [58]. Next, the KF algorithm calculates

$$\begin{aligned} \mathbb{E}\{r\} &= \int_{\eta=-\pi}^{\pi} p(\eta) \int_{\delta, \epsilon} r p(\delta, \epsilon) d\delta d\epsilon d\eta \\ &= \int_{\eta=0}^{\pi} \frac{1}{\pi} \int_{\delta, \epsilon} 0.5 \log(e^{2\delta} + e^{2\epsilon} + 2\cos(\eta)e^{\delta+\epsilon}) \\ &\quad \times p(\delta) p(\epsilon) d\delta d\epsilon d\eta, \end{aligned} \quad (23)$$

$$\begin{aligned} \mathbb{E}\{r^2\} &= \int_{\eta=0}^{\pi} \frac{1}{\pi} \int_{\delta, \epsilon} (0.5 \log(e^{2\delta} + e^{2\epsilon} \\ &\quad + 2\cos(\eta)e^{\delta+\epsilon}))^2 \times p(\delta) p(\epsilon) d\delta d\epsilon d\eta. \end{aligned} \quad (24)$$

The first two moments of $r_{t|t-1}$ are estimated with (23) and (24). Here, $K_{(\delta, \epsilon)}$ sigma points are used to evaluate the inner integral over (δ, ϵ) and K_{η} the outer integral over η [59].

C. The Non-Linear KF Update Step

The KF algorithm decomposes the noisy reverberant observation, y_t , into its component parts using distributions in the log-magnitude spectral domain. The decompositions are based on Fig. 2 and the signal model in (3) and (1) which allows the algorithm to perform a series of low-dimensional operations instead of a single high-dimensional one. The KF algorithm propagates backwards through Fig. 2 decomposing: (a) y_t into speech, s_t , and reverberation plus noise, z_t , (b) the reverberation plus noise, z_t , into reverberation, r_t , and noise, n_t , and (c) the reverberation, r_t , into “old reverberation”, δ_t , and “new reverberation”, ϵ_t . The reverberation plus noise, z_t , is a variable of the “KF Update” block shown in Fig. 3.

The KF algorithm in Fig. 3 uses y_t to first update s_t and z_t and then to update r_t . The posterior $z_{t|t}$ is computed in the “KF Update” block in Fig. 3. In the algorithm, the observed y_t affects $z_{t|t}$ directly and, in turn, $z_{t|t}$ affects $r_{t|t}$. We hence divide the observation update into two steps: (a) we use the log-spectrum observation, y_t , to estimate the posterior distributions $s_{t|t}$ and $z_{t|t}$ because $Y_t = S_t + Z_t$ in (3), and (b) we use $z_{t|t}$ as an “observation” to obtain the posterior distributions $r_{t|t}$ and $n_{t|t}$ because $Z_t = R_t + N_t$ in (3). In (b), we calculate an updated version of r_t by using the posterior $z_{t|t}$ as a KF observation constraint. According to (a) and (b), observing y_t provides new information about s_t and r_t .

The sequence of operations involved in the “Reverberation KF prediction”, “KF update” and “ γ_t, β_t KF update” blocks are listed in Table II. The “Reverberation KF prediction” block in Fig. 3, which was presented in Sec. III.B, performs

the first five operations. The “KF update” and “ γ_t, β_t KF update” blocks perform the next seven operations, i.e. steps 6-12, and the “ z^{-1} ” block performs step 13. These 13 steps constitute the dereverberation update step that computes the first two moments of the posterior distributions for most signal quantities and, moreover, includes the prediction step as well for some signal quantities. The means and variances of the tracked Gaussian signals are computed. For clarity, variances, such as $\Sigma_{t|t}^{(s)}$ for $s_{t|t}$ [52], are not included in Table II.

Table II

The operations performed in the “Reverberation KF prediction”, “KF Update” and “ γ_t, β_t KF Update” blocks in Fig. 3. Steps 7-12 perform specific signal decompositions propagating backwards through Fig. 2. Within the KF loop, the gray blocks in Fig. 3 track the signals s_t, r_t, γ_t and β_t .

Inputs: (a) $s_{t t-1}$ from the speech KF prediction step, (b) $n_{t t-}$ from external noise estimation, (c) y_t from observation, and (d) $s_{t-1 t}$ from $s_{t t}$ in step 7 and $\mathbf{B}_t^{-1}$ from Sec. III.A.	
1:	$\gamma_{t t-1} \leftarrow \gamma_{t-1 t-1}$ from step 13
2:	$\beta_{t t-1} \leftarrow \beta_{t-1 t-1}$ from step 13
3:	$\delta_{t t-1} \leftarrow \gamma_{t t-1}, r_{t-1 t-1}$ from steps 1, 13
4:	$\epsilon_{t t-1} \leftarrow \beta_{t t-1}, s_{t-1 t-1}$ from steps 2, 13
5:	$r_{t t-1} \leftarrow \delta_{t t-1}, \epsilon_{t t-1}$ from steps 3, 4
6:	$z_{t t-1} \leftarrow r_{t t-1}, n_{t t-}$ from step 5 and input (b)
7:	$s_{t t}, z_{t t} \leftarrow s_{t t-1}, z_{t t-1}, y_t$ from 6 and inputs (a), (c)
8:	$r_{t t}, [n_{t t}] \leftarrow r_{t t-1}, n_{t t-}, z_{t t}$ from 5, 7 and input (b)
9:	$\epsilon'_{t t} \leftarrow \beta_{t t-1}, s_{t-1 t}$ from step 2 and input (d)
10:	$\delta_{t t}, \epsilon_{t t} \leftarrow \delta_{t t-1}, \epsilon'_{t t}, r_{t t}$ from steps 3, 8, 9
11:	$\gamma_{t t}, [r_{t-1 t}] \leftarrow \gamma_{t t-1}, r_{t-1 t-1}, \delta_{t t}$ from steps 1, 10, 13
12:	$\beta_{t t}, [s_{t-1 t}] \leftarrow \beta_{t t-1}, s_{t-1 t}, \epsilon_{t t}$ from 2, 10 and input (d)
13:	$r_{t-1 t-1}, \gamma_{t-1 t-1}, \beta_{t-1 t-1} \leftarrow r_{t t}, \gamma_{t t}, \beta_{t t}$

For clarity, from this point onwards in Sec. III.C, the time subscript is included only if it differs from $t|t-1$. The prior and posterior time subscripts are presented in Table II.

The algorithm estimates the total disturbance, z_t , from (3) in step 6 using similar equations to step 5. A two-dimensional Gaussian distribution is used for $p(r, n)$ and independence is assumed between r and n . Hence, $p(r, n) = p(r)p(n)$. The phase-sensitive algorithm assumes that the phase difference, ζ , between the two disturbance sources, r and n , is uniformly distributed and independent of their magnitudes. Using a similar procedure to that used for r in (23), we can transform $Z_t = R_t + N_t$ from (3) into the form $e^{2z} = e^{2r} + e^{2n} + 2\cos(\zeta)e^{r+n}$ to obtain $z = 0.5 \log(e^{2r} + e^{2n} + 2\cos(\zeta)e^{r+n})$. Hence,

$$\begin{aligned} \mathbb{E}\{z\} &= \int_{\zeta=0}^{\pi} \frac{1}{\pi} \int_{r, n} 0.5 \log(e^{2r} + e^{2n} + 2\cos(\zeta)e^{r+n}) \\ &\quad \times p(r)p(n) dr dn d\zeta, \end{aligned} \quad (25)$$

$$\begin{aligned} \mathbb{E}\{z^2\} &= \int_{\zeta=0}^{\pi} \frac{1}{\pi} \int_{r, n} (0.5 \log(e^{2r} + e^{2n} \\ &\quad + 2\cos(\zeta)e^{r+n}))^2 \times p(r)p(n) dr dn d\zeta \end{aligned} \quad (26)$$

where $K_{(r, n)}$ sigma points are utilised to evaluate the inner integral over (r, n) [59] and K_{ζ} the outer integral over ζ .

The algorithm performs noise suppression with steps 6 and 7. Step 7 decomposes y_t into s_t and z_t , as shown in Fig. 2.

Step 7 performs the first signal decomposition, y_t into s_t and z_t , when propagating backwards through the signal model in Fig. 2. Step 7 applies the observation constraint, y_t , according to (3). As in [53] and [57], the variables are first transformed according to $(s, z, \lambda) \Rightarrow (u, y, \lambda)$ where $u = z - s$ and $\lambda = \angle S - \angle Z$. This variable transformation is performed to allow the imposition of the real-valued scalar observation, y_t .

Using a similar procedure to that used for z in (25), we can transform $Y_t = S_t + Z_t$ in (3) to obtain an expression for the noisy reverberant log-amplitude spectrum, y , as $y = s + 0.5 \log(1 + \exp(2(z - s))) + 2 \cos(\lambda) \exp(z - s)$. The KF update step assumes that $\angle Z$ is uniformly distributed, $\angle Z \sim U(-\pi, \pi)$. Hence, $\lambda \sim U(-\pi, \pi)$. The first two moments of the posteriors of s_t and z_t are computed in step 7 using

$$\begin{aligned} \mathbb{E}\{s_t^{m_1} z_t^{m_2} | \mathcal{Y}_t\} &= \int_{\lambda=-\pi}^{\pi} \int_{u=-\infty}^{\infty} s^{m_1} z^{m_2} p(u, \lambda | y_t) du d\lambda \\ &\propto \frac{1}{|\Delta|} \int_{\lambda=-\pi}^{\pi} p(\lambda) \int_{u=-\infty}^{\infty} s^{m_1} z^{m_2} p(s, z) du d\lambda \\ &\propto \int_{\lambda=0}^{\pi} \int_{u=-\infty}^{\infty} s^{m_1} z^{m_2} p(s)p(z) du d\lambda \end{aligned} \quad (27)$$

where $s = -0.5u + y - 0.5 \log(2 \cosh(u) + 2 \cos(\lambda))$ and $z = s + u$ [52]. The Jacobian determinant is $\Delta = -1$. The moment indices, m_1 and m_2 , are integers and $0 \leq m_1, m_2 \leq 2$.

The first two moments of the posterior distributions of s_t and z_t are estimated. In (27), the priors of the speech and of the noise and late reverberation are assumed to be independent, i.e. $p(s, z) = p(s)p(z)$. In addition, in (27), K_λ weighted sigma points are used to evaluate the outer integral over λ [52].

Step 8 performs the second signal decomposition, z_t into r_t and n_t , when propagating backwards through the proposed signal model in Fig. 2. Step 8 decomposes $z_{t|t}$ into r_t and n_t , according to (3), estimating both $r_{t|t}$ and $n_{t|t}$. It performs an integral over z_t where the integrand is similar to step 7 and (27) and to the KF update step in [53] [57]. Instead of a scalar observation, as in step 7, the observation in step 8 is a distribution; step 8 performs an outer integral over the observation distribution and the integrand is similar to step 7. Step 8 uses $\mathbb{E}\{r^m\} = \int_{z_t} \mathbb{E}\{r^m | z_t\} dz_t$ where $m \in \mathbb{N}_0$ and $0 \leq m \leq 2$. Step 7 computes a two-dimensional integral over the variables of $(z - s)$ and of the phase difference between S and Z , using y_t that reduces the probability space from three to two dimensions. In step 8, the KF algorithm calculates a three-dimensional integral over: (a) $(r - n)$, (b) the phase difference, $\iota = \angle R - \angle N$, between R and N , and (c) the posterior of z_t . Next, assuming $\angle N \sim U(-\pi, \pi)$ [52], step 8 computes

$$\begin{aligned} \mathbb{E}\{r_t^{m_1} n_t^{m_2} | \mathcal{Y}_t\} &\propto \int_{z=-\infty}^{\infty} p_{z_{t|t}}(z) \\ &\times \int_{\iota=0}^{\pi} \int_{u'=-\infty}^{\infty} r^{m_1} n^{m_2} p(r)p(n) du' d\iota dz \end{aligned} \quad (28)$$

where $u' = (r - n)$ and $\iota \sim U(-\pi, \pi)$. In (28), $z = r + 0.5 \log(1 + \exp(2(n - r))) + 2 \cos(\iota) \exp(n - r)$, $r = -0.5u' + z - 0.5 \log(2 \cosh(u') + 2 \cos(\iota))$ and $n = r + u'$ [52]. K_ι weighted sigma points are used to evaluate the integral over ι and $K_{z_{t|t}}$ sigma points to evaluate the integral over z [59]. In

step 8, the posterior of n_t is estimated using (28) but is not used in the KF recursion. In Table II, the signals in square brackets are computed but not used in the KF recursion.

Step 9 determines a preliminary estimate of the posterior distribution of the new reverberation component, ϵ_t , whose final estimate is calculated in step 10. This preliminary estimate, denoted $\epsilon'_{t|t}$, combines an updated estimate of the previous frame's speech, $s_{t-1|t}$, with the prior estimate of the reverberation parameter, $\beta_{t|t-1}$. The sub-indexes $t|t-1$ and $t-1|t$ give rise to the sub-index $t|t$. From (5), ϵ_t is the sum of two Gaussian random variables that are assumed to be independent and so we add their means and variances to obtain $\epsilon'_{t|t} = \beta_{t|t-1} + s_{t-1|t}$ and $\Sigma_{t|t}^{(\epsilon')} = \Sigma_{t|t-1}^{(\beta)} + \Sigma_{t-1|t}^{(s)}$.

Step 10 decomposes the reverberation, r_t , into a new reverberation component, ϵ_t and an old decaying reverberation component, δ_t , using (1), (4) and (5). Step 10 uses the prior distributions for these two components from steps 3 and 9. Step 10 performs the same operation as step 8. In analogy to step 7, the variable transformations in steps 8 and 10 are $(r, n, \iota) \Rightarrow (u', z, \iota)$ and $(\delta, \epsilon, \xi) \Rightarrow (u'', r, \xi)$, respectively. In step 10, the KF algorithm performs an integral over r where the integrand is similar to the KF update step in [53]. Step 10 estimates the posterior distributions of δ and ϵ ; it estimates both $\delta_{t|t}$ and $\epsilon_{t|t}$ using $\delta_{t|t-1}$ and $\epsilon'_{t|t}$. Step 10 computes

$$\begin{aligned} \mathbb{E}\{\delta_t^{m_1} \epsilon_t^{m_2} | \mathcal{Y}_t\} &\propto \int_{r=-\infty}^{\infty} p_{r_{t|t}}(r) \\ &\times \int_{\xi=0}^{\pi} \int_{u''=-\infty}^{\infty} \delta^{m_1} \epsilon^{m_2} p(\delta) p_{\epsilon'_{t|t}}(\epsilon) du'' d\xi dr \end{aligned} \quad (29)$$

where $u'' = (\delta - \epsilon)$ and $\xi \sim U(-\pi, \pi)$ is the phase difference of the STFT-domain signals of δ and ϵ . In (29), $\delta = -0.5u'' + r - 0.5 \log(2 \cosh(u'') + 2 \cos(\xi))$ and $\epsilon = \delta + u''$ for the inverse transformation of $(\delta, \epsilon, \xi) \Rightarrow (u'', r, \xi)$ [52]. Also, $r = \delta + 0.5 \log(1 + \exp(2(\epsilon - \delta))) + 2 \cos(\xi) \exp(\epsilon - \delta)$. We decompose $r_{t|t}$ into old reverberation and new reverberation, estimating both $\delta_{t|t}$ and $\epsilon_{t|t}$. K_ξ sigma points are used to evaluate the integral over ξ and $K_{r_{t|t}}$ sigma points the integral over r .

Steps 10-12 perform the final signal decomposition, r_t into γ_t and β_t , when propagating backwards through the signal model in Fig. 2. In steps 11 and 12, the KF algorithm computes the first two moments of the posterior distributions of γ_t and β_t . In step 11, the algorithm performs an integral over δ_t using weighted sigma points where the integrand models the addition of two random variables in the log-amplitude spectral domain, γ_t and r_{t-1} . Likewise, in step 12, the algorithm performs an integral over ϵ_t using sigma points where the integrand models the addition of two random variables in the log-amplitude spectral domain, β_t and s_{t-1} . Steps 11 and 12 perform a linear KF update and impose a straight line observation constraint because the signal model is that γ_t and r_{t-1} are additive and that β_t and s_{t-1} are additive, according to (4) and (5).

In step 11, the non-linear KF algorithm decomposes the old reverberation component, δ_t , according to (4) into the sum of a reverberation parameter, γ_t , and the previous frame's reverberation, r_{t-1} . We now define $\mathbf{x}_1 \sim \mathcal{N}(\mathbf{x}_1; \boldsymbol{\mu}_1, \mathbf{S}_1)$ where $\mathbf{x}_1 = (\gamma_t, r_{t-1}, w_t)^T \in \mathbb{R}^3$, where w_t is zero-mean Gaussian with variance $\Sigma_t^{(\delta)}$, $\boldsymbol{\mu}_1 = (\gamma_{t|t-1}, r_{t-1|t-1}, 0)^T \in \mathbb{R}^3$ and

$\mathbf{S}_1 = \text{diag}((\Sigma_{t|t-1}^{(\gamma)}, \Sigma_{t-1|t-1}^{(r)}, \Sigma_{t|t}^{(\delta)})^T) \in \mathbb{R}^{3 \times 3}$ where $\text{diag}(\mathbf{j})$ is a diagonal matrix with the elements of the vector $\mathbf{j}$ on the main diagonal. If $\mathbf{x}_1 \sim \mathcal{N}(\mathbf{x}_1; \boldsymbol{\mu}_1, \mathbf{S}_1)$, then we can write,

$$(\mathbf{x}_1 | \mathbf{g}^T \mathbf{x}_1 = \delta_{t|t}) \sim \mathcal{N}(\mathbf{x}_1; (\mathbf{I} - \mathbf{H}_1 \mathbf{g}^T) \boldsymbol{\mu}_1 + \mathbf{H}_1 \delta_{t|t}, (\mathbf{I} - \mathbf{H}_1 \mathbf{g}^T) \mathbf{S}_1) \quad (30)$$

where $\mathbf{H}_1 = \mathbf{S}_1 \mathbf{g} (\mathbf{g}^T \mathbf{S}_1 \mathbf{g})^{-1}$ and $\mathbf{g} = (1, 1, -1)^T \in \mathbb{R}^3$ [60]. We compute $(\mathbf{I} - \mathbf{H}_1 \mathbf{g}^T) \boldsymbol{\mu}_1 + \mathbf{H}_1 \delta_{t|t} \in \mathbb{R}^3$ and $(\mathbf{I} - \mathbf{H}_1 \mathbf{g}^T) \mathbf{S}_1 \in \mathbb{R}^{3 \times 3}$ and set $\gamma_{t|t}$ equal to the first element of this computed mean and $\Sigma_{t|t}^{(\gamma)}$ equal to the first element of this variance.

Likewise, for step 12, we define $\mathbf{x}_2 \sim \mathcal{N}(\mathbf{x}_2; \boldsymbol{\mu}_2, \mathbf{S}_2)$ where $\mathbf{x}_2 = (\beta_t, s_{t-1}, q_t)^T \in \mathbb{R}^3$, q_t is zero-mean Gaussian with variance $\Sigma_t^{(\epsilon)}$, $\boldsymbol{\mu}_2 = (\beta_{t|t-1}, s_{t-1|t}, 0)^T \in \mathbb{R}^3$ and, using (5), $\mathbf{S}_2 = \text{diag}((\Sigma_{t|t-1}^{(\beta)}, \Sigma_{t-1|t}^{(s)}, \Sigma_{t|t}^{(\epsilon)})^T) \in \mathbb{R}^{3 \times 3}$. Next, we use

$$(\mathbf{x}_2 | \mathbf{g}^T \mathbf{x}_2 = \epsilon_{t|t}) \sim \mathcal{N}(\mathbf{x}_2; (\mathbf{I} - \mathbf{H}_2 \mathbf{g}^T) \boldsymbol{\mu}_2 + \mathbf{H}_2 \epsilon_{t|t}, (\mathbf{I} - \mathbf{H}_2 \mathbf{g}^T) \mathbf{S}_2) \quad (31)$$

where $\mathbf{H}_2 = \mathbf{S}_2 \mathbf{g} (\mathbf{g}^T \mathbf{S}_2 \mathbf{g})^{-1}$ [60]. The KF algorithm computes $(\mathbf{I} - \mathbf{H}_2 \mathbf{g}^T) \boldsymbol{\mu}_2 + \mathbf{H}_2 \epsilon_{t|t} \in \mathbb{R}^3$ and $(\mathbf{I} - \mathbf{H}_2 \mathbf{g}^T) \mathbf{S}_2 \in \mathbb{R}^{3 \times 3}$ and sets $\beta_{t|t}$ equal to the first element of this computed mean and $\Sigma_{t|t}^{(\beta)}$ equal to the first element of this computed variance. In steps 11 and 12, we compute $\gamma_{t|t}$, $\Sigma_{t|t}^{(\gamma)}$ and $\beta_{t|t}$, $\Sigma_{t|t}^{(\beta)}$, respectively, using both $p(\gamma_t, r_{t-1} | \delta_{t|t} + w_t)$ and $p(\beta_t, s_{t-1} | \epsilon_{t|t} + q_t)$.

Finally, step 13 in Table II applies a one-frame delay, z^{-1} , in order to continue the KF recursion, as shown in Fig. 3.

D. Discussion of the Non-Linear KF Update Step

Section III.C presented the operations performed in the update step. This section discusses these operations that track the log-spectra of speech and reverberation blindly and adaptively. Steps 7 to 12 of Table II use y_t to update in sequence the probability distributions of s_t , z_t , r_t , n_t , δ_t , ϵ_t , γ_t and β_t by tracing backwards through the block diagram in Fig. 2.

According to the 13 steps, γ_t and β_t are affected by y_t through a series of operations that estimate the first two moments of the posterior distributions. The estimate of γ_t is affected by the previous estimate of β_t because of the sequence of operations $\beta_{t-1|t-1} \Rightarrow \beta_{t|t-1} \Rightarrow \epsilon'_{t|t} \Rightarrow \delta_{t|t} \Rightarrow \gamma_{t|t}$. Likewise, the estimate of β_t depends on the previous estimate of γ_t because $\gamma_{t-1|t-1} \Rightarrow \gamma_{t|t-1} \Rightarrow \delta_{t|t-1} \Rightarrow \epsilon_{t|t} \Rightarrow \beta_{t|t}$.

Step 7 starts from a distribution in the three-dimensional probability space, performs a specific variable transformation, imposes the KF observation constraint [52] and ends with a distribution in the two-dimensional probability space. Step 7 computes both $s_{t|t}$ and $z_{t|t}$ and is based on the non-linear KF update step presented in [53]. The algorithm presented in this section, for joint denoising and dereverberation, generalizes the algorithm presented in [53]. It can be stated that the update step described in [52] could be used in step 7 in Table II in lieu of the update step detailed in [53]. This would result in tracking the speech phase and performing dereverberation.

In steps 7 and 8, the algorithm estimates $s_{t|t}$, $r_{t|t}$ and $n_{t|t}$ and their variances, $\Sigma_{t|t}^{(s)}$, $\Sigma_{t|t}^{(r)}$ and $\Sigma_{t|t}^{(n)}$. The posterior means of speech, reverberation and noise given y_t are more accurate estimates of speech, reverberation and noise than the estimates produced by the unshaded peripheral blocks in Fig. 3.

The proposed 13 steps do not include the speech prediction step shown in Fig. 3, which is used to calculate $s_{t-1|t}$ that is needed in steps 9 and 12. After step 7, according to Fig. 3 and Sec. III.B, recorrelation of the speech KF state is performed. Using $s_{t|t}$, from the recorrelation step, $s_{t-1|t}$ is obtained and $s_{t-1|t}$ is used as a better estimate of s_{t-1} than $s_{t-1|t-1}$.

Steps 11 and 12 estimate $\gamma_{t|t}$ and $\beta_{t|t}$ together with their variances, $\Sigma_{t|t}^{(\gamma)}$ and $\Sigma_{t|t}^{(\beta)}$. Joint denoising and dereverberation using external reverberation parameter estimation could be performed using a simplified version of the algorithm in Fig. 3. An external T_{60} and DRR estimator, such as [61] [62], could be used instead of tracking γ_t and β_t in (4) and (5), outside the KF loop, not in an online adaptive manner. Batch processing could be used for reverberation parameter estimation and the T_{60} and the DRR could be assumed time-invariant [15].

E. The Priors for the Reverberation Parameters

This section describes the priors for γ_t and β_t based on [63] [64] and [61]. These priors are imposed using Gaussian-Gaussian multiplication; γ_t is modelled with a Gaussian distribution and its internal prior is also a Gaussian. Likewise, β_t is modelled with a Gaussian and its prior is a Gaussian.

The priors for γ_t and β_t are estimated from spectral log-amplitude observations in the free decay region (FDR), which comprises M_t consecutive frames with decreasing energy. We define the look-ahead time interval, C , and the frame index $l = t - M_t + C + 1, t - M_t + C + 2, \dots, t + C$. The least squares (LS) fit to the FDR is found using $r_l = \theta_1 x_l + \theta_2$ where x_l is the time index in seconds and depends on L . The parameters of the straight line are the slope, θ_1 , and the y-intercept, θ_2 . For clarity, the time subscript, t , is omitted from θ_1 and θ_2 . We define $\boldsymbol{\theta} = (\theta_1 \ \theta_2)^T \in \mathbb{R}^2$. Its Gaussian distribution is

$$\mathcal{N}(\boldsymbol{\theta}; \boldsymbol{\mu}_\theta, \boldsymbol{\Sigma}_\theta) \propto |\boldsymbol{\Sigma}_\theta|^{-0.5} \times \exp(-0.5(\boldsymbol{\theta} - \boldsymbol{\mu}_\theta)^T \boldsymbol{\Sigma}_\theta^{-1} (\boldsymbol{\theta} - \boldsymbol{\mu}_\theta)) \quad (32)$$

where $\boldsymbol{\mu}_\theta \in \mathbb{R}^2$ and the covariance matrix is $\boldsymbol{\Sigma}_\theta \in \mathbb{R}^{2 \times 2}$.

The log-likelihood of $\boldsymbol{\theta}$ is given by $l(\boldsymbol{\theta}) = c_1 - 0.5(\boldsymbol{\theta} - \boldsymbol{\mu}_\theta)^T \boldsymbol{\Sigma}_\theta^{-1} (\boldsymbol{\theta} - \boldsymbol{\mu}_\theta) = c_2 - 0.5 \sum_{\tau=t-M_t+C+1}^{t+C} ((\theta_1 x_\tau + \theta_2 - r_\tau)^T (\boldsymbol{\Sigma}_\tau^{(r)})^{-1} (\theta_1 x_\tau + \theta_2 - r_\tau))$ where c_1 and c_2 are constants.

We define the vectors $\mathbf{x} \in \mathbb{R}^{M_t}$ and $\mathbf{r} \in \mathbb{R}^{M_t}$ from x_l and r_l , respectively. We define $\boldsymbol{\Sigma}_r \in \mathbb{R}^{M_t \times M_t}$ as the covariance matrix of $\mathbf{r}$. The regression coefficients as a Gaussian distribution are $\mathcal{N}(\boldsymbol{\theta}; \boldsymbol{\mu}_\theta, \boldsymbol{\Sigma}_\theta)$ where $\boldsymbol{\mu}_\theta = \mathbf{A}^{-1} \mathbf{b}$ and $\boldsymbol{\Sigma}_\theta = \mathbf{A}^{-1}$,

$$\mathbf{A} = \begin{pmatrix} \mathbf{x}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{x} & \mathbf{x}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{1} \\ \mathbf{1}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{x} & \mathbf{1}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{1} \end{pmatrix}, \quad (33)$$

$$\mathbf{b} = \begin{pmatrix} \mathbf{x}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{r} \\ \mathbf{1}^T \boldsymbol{\Sigma}_r^{-1} \mathbf{r} \end{pmatrix} \quad (34)$$

where $\mathbf{1} \in \mathbb{R}^{M_t}$ is a vector of ones. Figure 4 shows the log-likelihood of the Gaussian distribution of $\boldsymbol{\theta}$ with mean $\boldsymbol{\mu}_\theta$ and variance $\boldsymbol{\Sigma}_\theta$ when the correlation between θ_1 and θ_2 is strong. We note that the maximum likelihood solution for the mean of θ_1 , when θ_2 is not considered, can be found in [65].

The noisy reverberation, z_t , is the observation and, in this case, our aim is to find r_t and $\Sigma_t^{(r)}$. We denote the noise floor in the power spectral domain by $|N|^2$ and we define the RNR

as $\text{RNR} = \exp(2(r - n))$. In a FDR, at high RNRs and when $|N|^2$ is low, $r_t \approx z_t$ because $z = r + 0.5 \log(1 + \text{RNR}^{-1} + 2 \cos(\zeta) \text{RNR}^{-0.5})$ from (25) and (26), using ζ as in [52].

To find r_t and $\Sigma_t^{(r)}$ given the observed z_t , we first employ a minimum MSE (MMSE) algorithm, such as the Log-MMSE estimator [37], to attenuate the noise and estimate the signal's spectrum, as in [61], and then perform a KF update step and use z_t as the KF observation. For the linear KF [66] [67], when the observation noise covariance matrix tends to zero at high RNRs, then the mean of the state goes to the KF observation and the variance of the state goes to zero. A solution to the problem of finding r_t and $\Sigma_t^{(r)}$ is to set $r_t = z_t$ and to also set $\Sigma_t^{(r)}$ equal to a fixed small value, such as 1 dB².

The T_{60} can be estimated from θ_1 using $T_{60} = -\frac{3 \log(10)}{\theta_1}$, where θ_1 is computed from FDR data in the log-magnitude spectral domain [64]. The KF algorithm, which models γ_t with a Gaussian distribution, uses a Gaussian prior for γ with mean $L\mu_{\theta_1}$ and variance $L^2\Sigma_{\theta_1}$ because $\gamma = L\theta_1$. Using $\gamma = L\theta_1$, θ_1 is directly mapped to γ_t , without going via the T_{60} .

The algorithm estimates a prior for β_t at the same time as the prior for γ_t . Figure 5 depicts y_t , s_t and r_t over time, at 1 kHz, when the noise is white, the reverberant speech to noise ratio (RSNR) is 20 dB, the T_{60} is 0.68 s and the DRR is -2.52 dB. In Fig. 5, s_t and r_t are the true speech and reverberation powers; the latter is computed by convolving the RIR without its first 30 ms with the speech signal [2]. If we choose an appropriate FDR, then (1) and (2) are related to the FDR and the first frame of the FDR to the DRR. Here, β is computed from the difference between the log-amplitude of the first frame and the r -intercept of the LS fit, i.e. θ_2 . For the subtraction of two independent random variables, their means subtract and their variances add; θ_2 has a mean and a variance and the log-amplitude of the first frame of the FDR has a mean and a fixed small variance. The prior for β_t is given by

$$\beta_t = r_{t-M_t+C+1} - \theta_2. \quad (35)$$

We denote the mean of the internally computed Gaussian γ_t prior by $\gamma_{t|t-1}^{(\gamma')}$ and its variance by $\Sigma_{t|t-1}^{(\gamma')}$. The KF uses

$$\gamma_{t|t-1} = \frac{\gamma'_{t|t-1} \Sigma_{t|t-1}^{(\gamma'')} + \gamma''_{t|t-1} \Sigma_{t|t-1}^{(\gamma')}}{\Sigma_{t|t-1}^{(\gamma')} + \Sigma_{t|t-1}^{(\gamma'')}}, \quad (36)$$

$$\Sigma_{t|t-1}^{(\gamma)} = \frac{\Sigma_{t|t-1}^{(\gamma')} \Sigma_{t|t-1}^{(\gamma'')}}{\Sigma_{t|t-1}^{(\gamma')} + \Sigma_{t|t-1}^{(\gamma'')}}. \quad (37)$$

Likewise, we denote the mean of the Gaussian β_t prior by $\beta_{t|t-1}^{(\beta')}$ and its variance by $\Sigma_{t|t-1}^{(\beta')}$. For β_t in (5) and Fig. 1,

$$\beta_{t|t-1} = \frac{\beta'_{t|t-1} \Sigma_{t|t-1}^{(\beta'')} + \beta''_{t|t-1} \Sigma_{t|t-1}^{(\beta')}}{\Sigma_{t|t-1}^{(\beta')} + \Sigma_{t|t-1}^{(\beta'')}}, \quad (38)$$

$$\Sigma_{t|t-1}^{(\beta)} = \frac{\Sigma_{t|t-1}^{(\beta')} \Sigma_{t|t-1}^{(\beta'')}}{\Sigma_{t|t-1}^{(\beta')} + \Sigma_{t|t-1}^{(\beta'')}}. \quad (39)$$

Blind T_{60} estimation, when the RIR is unknown [68], is not straightforward. The KF algorithm estimates the T_{60} using (32)-(39) and the decay rate of the LS fit to the FDR [64] so that the KF does not diverge and does not treat r_t as s_t .

Figure 4. Plot of the log-likelihood of the Gaussian distribution of θ in (32). $\Sigma_\theta = \mathbf{A}^{-1}$ is non-diagonal. $\mathbf{A}$ is computed in (33) from the FDR.

Figure 5. Plot of the true s_t , of y_t and of the true r_t at 1 kHz when the noise is white, SNR = 20 dB, $T_{60} = 0.68$ s and DRR = -2.52 dB.

F. The Peripheral Blocks of the Algorithm

This section describes the unshaded blocks in Fig. 3 that lie outside the KF loop. The algorithm uses pre-cleaning before performing speech AR modelling, as in [52] and [67], and pre-cleaning is also used in [50] [51] and in [10] [54]. The “Speech pre-cleaning” block in Fig. 3 affects the “Speech KF prediction” block and not the observation of the “KF Update” block, i.e. y_t , which is used in step 7 in Table II. Speech amplitude spectrum pre-cleaning, which is scale independent [11], is performed before the “sliding-window” AR modeling in the log-spectral domain. The “pre-cleaning” block applies a conventional enhancement algorithm, such as the Log-MMSE enhancer [37] followed by the WPE dereverberation algorithm [69] [70], to the noisy speech so that speech AR modeling can be performed. The speech AR coefficients are estimated from noisy reverberant speech and their estimate is biased [29] and this model mis-specification is fixed by pre-cleaning [50]. Although it would be possible to use the enhanced signal from the KF output when estimating the AR coefficients, we have chosen not to do so to avoid the risk of instability [71].

For the “Noise power estimation” block, an external noise power estimator, such as [72], is used. External noise estimation and log-normal noise power modelling, as in [73] [74], are used for $n_{t|t-}$, which is then used in step 6 of Table II. The purpose of the external noise estimator is to remove ambiguity when jointly estimating the log-magnitude spectra of speech, noise and reverberation in steps 7 and 8. The noise estimator, which is out of the KF loop in Fig. 3, provides a mechanism that helps the algorithm distinguish between speech, noise and reverberation. Without additional information, estimating the first two moments of the posterior distributions of s_t , n_t and r_t given the real-valued y_t is an ill-conditioned problem.

In summary, the KF algorithm tracks speech and reverberation in the log-magnitude spectral domain along with γ_t and β_t , as described in Fig. 3 and in the signal model in Fig. 2.

IV. IMPLEMENTATION, TESTING AND VALIDATION

We use acoustic frames of length 32 ms and an acoustic frame increment of $L = 8$ ms in (2). We also use modulation frames of 64 ms and a modulation frame increment of 8 ms [52] [54]. The dimension of the speech KF state, s_t , in (6) is $p = 2$ resulting in a total KF state dimension of 5 when the reverberation parameters, r_t , γ_t and β_t , are included. In Fig. 3, for pre-cleaning, we use the Log-MMSE enhancer [37]

Figure 6. Plot of the predicted and true: (a) speech power, i.e. $s_{t|t}$ and the true s_t , at 1 kHz, (b) noise and reverberation power, i.e. $z_{t|t}$ and the true z_t , at 1 kHz, (c) reverberation power, i.e. $r_{t|t}$ and the true r_t , at 1 kHz, and (d) T_{60} and DRR reverberation parameters. In (a)-(d), the T_{60} is 0.61 s and the DRR is -1.74 dB, while the noise type is white and the RSNR is 20 dB.

(implemented in [75]) followed by the WPE dereverberation algorithm [69] [70]. In the “Noise power estimation” block of Fig. 3, we use the unbiased MMSE-based noise estimator from [72] (implemented in [75]), as in [10], [11] and [52].

In Sec. III.B, the random-walk parameters, Q_γ and Q_β , are set to fixed values that are chosen so that the standard deviation corresponds to a rate of change of the T_{60} and the DRR of 10% per second. If it is known that the acoustic environment is static, the reverberation parameters can be taken to be time-invariant and estimated offline. In this case, we can set $Q_\gamma = Q_\beta = 0$ and omit steps 11 and 12 from Table II. In realistic situations, however, the movement of people and the opening of doors or windows mean that the reverberation parameters are inconstant and should be tracked in the algorithm.

The outer integrals in Secs. III.B and III.C are performed using sigma points, as in [52]. The numbers of sigma points used in (23)-(29) are $K_{(\delta,\epsilon)} = K_{(r,n)} = K_{z_{t|t}} = K_{r_{t|t}} = 3$ and $K_\eta = K_\zeta = K_\lambda = K_\iota = K_\xi = 6$. For the latter cases, for ξ , the sigma points are at $\xi = ((1 : K_\xi) - 0.5) \frac{\pi}{K_\xi}$ and the weights are all equal to $\frac{1}{K_\xi}$ [52] [53]. With this choice of sigma points for ξ , the integral will be exact for an integrand that is a sum of terms of the form $\cos(n\xi)$ for $0 \leq n \leq 2K_\xi + 1$.

In Sec. III.E, for the γ_t and β_t priors, the look-ahead factor is $C = 3$ frames. For the FDR that is comprised of frames with decreasing energy, M_t is computed in every frame.

Figures 6(a)-(c) show the time variation of s_t , z_t and r_t in the 1 kHz bin, as in [67]. Figure 6(a) depicts the predicted and true speech power, i.e. $s_{t|t}$ and the true s_t , and Fig. 6(b) the predicted and true noise plus reverberation power, i.e. $z_{t|t}$ and the true z_t . The correlation coefficient between the true z_t and $z_{t|t}$ is 0.89. Figure 6(c) shows the predicted and true reverberation power, i.e. $r_{t|t}$ and the true r_t . The correlation coefficient between the true r_t and $r_{t|t}$ is 0.77 (< 0.89). The

ordering of the graphs in Figs. 6(a)-(c) matches the ordering of the signal decompositions in the KF algorithm, in Table II. The noisy reverberant log-spectrum is first decomposed into s_t and z_t with step 7; Figs. 6(a) and (b) illustrate $s_{t|t}$ and $z_{t|t}$, respectively, over time. Then, $z_{t|t}$ is decomposed into r_t and n_t with step 8 and Fig. 6(c) depicts $r_{t|t}$ over time. Here, RSNR = 20 dB white noise, $T_{60} = 0.61$ s and DRR = -1.74 dB.

The T_{60} and DRR estimates should converge to their true constant values when both the talker and the microphone are not moving and the frequency variations in the reflection coefficients are not modelled [76] [77]. The internally estimated priors for γ_t and β_t make the reverberation parameters converge over time. Figure 6(d) shows the predicted and true T_{60} and DRR reverberation parameters and the ground truth values are shown as horizontal lines [5]. The dashed lines are the signals’ standard deviations computed from γ_t and β_t .

V. EVALUATION OF THE ALGORITHM

The KF algorithm is evaluated in terms of the perceptual evaluation of speech quality (PESQ) [78], the cepstral distance (CD) spectral divergence metric [79], the reverberation decay tail (RDT) dereverberation metric [80] and the STOI speech intelligibility metric [81] [82]. The ideal values of CD and RDT, which were also used in [20] [21], are zero. For evaluation, the TIMIT database [83], sampled at 16 kHz, and the RSG-10 noise database [84] are used. From the TIMIT database, 52 utterances are chosen. We use artificially-created reverberation with the image method [76] using the implementation in [85] [9]. The wall reflection coefficient is adjusted to vary the T_{60} and the DRR. The adaptive KF algorithm is evaluated with noisy reverberant speech at various RSNRs [86], using random noise segments and white, babble and factory noises.

The KF algorithm is compared to the SPENDRED algorithm [20] [21], which jointly performs blind denoising and dereverberation, and to algorithms that sequentially perform denoising and dereverberation, specifically to the Log-MMSE estimator [37] followed by the WPE algorithm [70] [31] and to the Log-MMSE estimator followed by an inverse-filter (IF) dereverberation method based on T_{60} and DRR estimates. For the Log-MMSE enhancer followed by the WPE algorithm, we also evaluated applying WPE followed by Log-MMSE but found that this reverse order leads to marginally worse enhancement results, averaging -0.02 in PESQ. For the IF, we blindly estimate the T_{60} and the DRR for the entire utterance using the algorithm in [61] [62], whose implementation was generously provided by the author. As found in [1], the T_{60} estimator in [61] had the best performance of the examined estimators. We apply a dereverberation post-filter to the output of a Log-MMSE enhancer using the T_{60} and DRR estimates. Assuming that a and b in (2) are time-invariant and frequency-independent, using a reverberation model in the power spectral domain [20] [21], if $|\hat{S}_t|^2$ is the output power from Log-MMSE, then $|S_t|^2 = (a - b)|S_{t-1}|^2 + |\hat{S}_t|^2 - a|\hat{S}_{t-1}|^2$.

For evaluation, the examined acoustic conditions are shown in Table III. Two different rooms with dimensions $5 \times 4 \times 4$ m and $10 \times 7 \times 3$ m are used. The distance between the microphone and the talker is 1.5 m. Table III is sorted with

Table III

List of the environments sorted with respect to the T_{60} from A to I and from J to V. The room dimensions are $5 \times 4 \times 4$ or $10 \times 7 \times 3$ m. The source-microphone distance is 1.5 m. The wall reflection coefficient is adjusted to vary the T_{60} and the DRR. For a and b in (2), $L = 8$ ms.

Index	T_{60} (s)	DRR (dB)	Room (m×m×m)	a	b
A	0.18	8.43	$5 \times 4 \times 4$	0.54	0.07
B	0.25	5.78	$5 \times 4 \times 4$	0.64	0.10
C	0.33	3.13	$5 \times 4 \times 4$	0.72	0.14
D	0.40	1.69	$5 \times 4 \times 4$	0.76	0.16
E	0.47	0.25	$5 \times 4 \times 4$	0.79	0.20
F	0.54	-0.74	$5 \times 4 \times 4$	0.81	0.23
G	0.61	-1.74	$5 \times 4 \times 4$	0.83	0.25
H	0.64	-2.13	$5 \times 4 \times 4$	0.84	0.26
I	0.68	-2.52	$5 \times 4 \times 4$	0.85	0.27
J	0.21	8.07	$10 \times 7 \times 3$	0.59	0.06
K	0.31	2.74	$10 \times 7 \times 3$	0.70	0.16
L	0.40	0.17	$10 \times 7 \times 3$	0.76	0.23
M	0.50	0.11	$10 \times 7 \times 3$	0.80	0.19
N	0.59	-0.73	$10 \times 7 \times 3$	0.83	0.20
O	0.64	-0.95	$10 \times 7 \times 3$	0.84	0.20
P	0.69	-1.12	$10 \times 7 \times 3$	0.85	0.19
Q	0.71	-1.68	$10 \times 7 \times 3$	0.86	0.21
R	0.73	-2.01	$10 \times 7 \times 3$	0.86	0.22
S	0.85	-2.09	$10 \times 7 \times 3$	0.88	0.19
T	0.97	-2.95	$10 \times 7 \times 3$	0.89	0.22
U	1.01	-3.11	$10 \times 7 \times 3$	0.90	0.20
V	1.05	-3.33	$10 \times 7 \times 3$	0.90	0.22

respect to the T_{60} and the DRR from A to I and from J to V. We plot the improvement in PESQ, Δ PESQ, against the index of the acoustic environment to evaluate the KF algorithm. The top axis shows the raw PESQ of the noisy reverberant speech and is monotonic from A to I and from J to V. Similar graphs are also plotted for the other metrics. The ordering of the legends matches that of the algorithms at low T_{60} values.

Table III also shows the a and b reverberation values of the RIRs and we note that the SPENDRED algorithm [20] [21] assumes that $b \leq 1$. This is valid in Table III since $b \ll 1$.

A. Overall Performance Against the T_{60} and the DRR

This section investigates the performance of the algorithm against the T_{60} and the DRR. Figure 7 shows: (a) the Δ PESQ, where higher scores signify better speech quality, (b) the Δ CD, where lower values signify better speech quality, (c) the Δ RDT, where lower values signify better dereverberation, and (d) the Δ STOI, where higher scores signify better intelligibility. Figure 7 first presents the results that are related to speech quality, in (a) and (b). Then, it shows the dereverberation results, in (c), and the speech intelligibility results, in (d). The graphs are against the index of the acoustic environment and, hence, against the T_{60} and the DRR. The average over the white, babble and factory noises at 20 dB RSNR is shown.

In Fig. 7(a), the top axis presents the raw PESQ of the unenhanced signal and is monotonic from A to I and from J to V; there is no transition between index I and index J.

From Fig. 7(a), the algorithm consistently yields improved PESQ quality in challenging conditions compared to the baselines. Compared to the unprocessed signal, the algorithm shows improved performance for all the examined T_{60} range from 0.18 to 1.05 s and DRR range from 8.43 to -3.33 dB. Compared to the unprocessed signal, for a T_{60} of 0.3 and 1 s,

Figure 7. Plot of: (a) Δ PESQ where higher scores signify better speech quality, (b) Δ CD where lower values signify better speech quality, (c) Δ RDT where lower values signify better dereverberation, and (d) Δ STOI where higher scores signify better intelligibility. The graphs are against the index of the acoustic environment and, hence, against the T_{60} and the DRR. The mean over the noises of white, babble and factory at 20 dB RSNR is shown.

the algorithm has a Δ PESQ of 0.35 and 0.25, respectively, for the RSNR of 20 dB averaged over the examined noises.

From Fig. 7(b), in terms of CD, the KF algorithm yields improved speech quality in acoustic environments with a T_{60} from 0.18 to 1.05 s. The KF algorithm shows a deteriorating CD improvement with increasing T_{60} . Compared to the unprocessed signal, for a T_{60} of 0.3 and 1 s, the algorithm has a CD improvement of approximately -1.1 and -0.6, respectively, for 20 dB RSNR averaged over the tested noise types.

From Fig. 7(c), we observe that the KF algorithm yields improved speech dereverberation in challenging acoustic conditions and that the Δ RDT improves with increasing T_{60} values. From the raw RDT of noisy reverberant speech in Fig. 7(c), we observe that the indexes A and J have very low reverberation. The indexes A and J have raw RDT scores 0.4 and 0.7, respectively. The indexes G-I and T-V have high reverberation with a high raw RDT score. The proposed algorithm in these high reverberation cases achieves a large RDT improvement decreasing the RDT metric from approximately 2.6 to 0.8.

From Fig. 7(d), the algorithm shows marginally improved STOI performance for the tested T_{60} range compared to the unprocessed signal and to the examined baselines. For a T_{60} of 0.3 and 1 s, the algorithm has a Δ STOI of 0.03 and 0.07, respectively. Δ STOI slightly increases with increasing T_{60} .

Figure 8 shows the same graphs as in Fig. 7 but for a RSNR of 10 dB. For the examined T_{60} values and for white, babble and factory noises, the KF algorithm shows a consistent improvement in the PESQ, CD, RDT and STOI metrics.

Figure 9 depicts the same set of graphs as in Figs. 7 and 8 but for a RSNR of 5 dB. For all the examined RSNRs, the KF algorithm shows a consistent improvement in the examined metrics, depending on the T_{60} . From Fig. 9(a), we observe that

Figure 8. Plot of: (a) Δ PESQ, (b) Δ CD, (c) Δ RDT, and (d) Δ STOI. The graphs are against the index of the acoustic environment. The average over the noise types of white, babble and factory at 10 dB RSNR is shown.

Figure 9. Plot of: (a) Δ PESQ, (b) Δ CD, (c) Δ RDT, and (d) Δ STOI. The graphs are against the index of the acoustic environment. The average over the noise types of white, babble and factory at 5 dB RSNR is shown.

the Δ PESQ scores of the algorithm at 5 dB RSNR are similar to the Δ PESQ scores at 10 dB RSNR shown in Fig. 8(a).

The KF algorithm shows improved PESQ performance for the examined RSNRs from 5 dB to 20 dB. The algorithm has better speech quality performance compared to the baselines for all the examined T_{60} values. Compared to the unprocessed noisy reverberant speech, for the RSNR of 5 dB, the algorithm has a Δ PESQ of about 0.45 for a T_{60} of 0.6 s and a raw PESQ of 1.6. For the RSNR of 20 dB, the algorithm has a Δ PESQ of approximately 0.3 for a T_{60} of 0.6 s and a raw PESQ of 2. Comparing Figs. 7-9, we observe that the raw PESQ decreases with decreasing RSNR while the Δ PESQ scores increase.

Figure 10. Plot of Δ LLR where lower scores signify better speech quality when white noise is used: (a) at 20 dB RSNR, and (b) at 10 dB RSNR.

The KF algorithm yields improved dereverberation performance in terms of RDT in adverse conditions in Fig. 9(c). The algorithm's performance improves with decreasing RSNR. We observe that the indexes A-C and J-K have a high raw RDT despite that they have low reverberation at 5 dB RSNR, when the effect of noise is higher than that of reverberation.

Figure 10 shows the log-likelihood ratio (LLR) when white noise is used at 20 and 10 dB RSNR. Decreasing the RSNR from 20 to 10 dB increases the raw LLR of noisy reverberant speech and deteriorates the Δ LLR. The results of LLR [87], which has been used to evaluate the dereverberation algorithm in [86], resemble the results of CD. Both CD and LLR have been used in [4]. It was found in [88] that LLR correlates well with speech quality although slightly less well than PESQ.

B. Overall Performance Against the RSNR

This section investigates the performance of the algorithm against the RSNR. If the reverberation is counted as additional noise, the overall SNR is always less than both the RSNR and the DRR. Figure 11 presents the algorithm's performance compared to the tested baselines for RSNRs from 0 to 20 dB. Figures 11(a) and 11(b) depict the Δ PESQ for white noise when: (a) $T_{60} = 0.40$ s and DRR = 0.17 dB, which is case L in Table III, and (b) $T_{60} = 0.73$ s and DRR = -2.1 dB, which is case R. The indexes L and R were chosen because they have different T_{60} and DRR values. The ordering of the legends in Fig. 11 matches that of the algorithms at high RSNRs.

Figures 11(c) and 11(d) illustrate the Δ PESQ against the RSNR, from 0 to 20 dB, for babble and factory noises, for cases L and R in Table III respectively, for the KF algorithm compared to the baselines. Babble noise is used for the solid lines, the top axis and the legends; factory noise is used for the dashed lines. The Δ PESQ depends on the RSNR and the noise type and is, most of the times, increasing with decreasing RSNRs. Compared to the unprocessed speech in Fig. 11(c), the algorithm's Δ PESQ is approximately 0.35 for factory noise for high RSNRs, while it is decreasing for lower RSNRs.

Figure 12 examines the RDT improvement, Δ RDT, against the RSNR, from 0 to 20 dB, for white noise, for cases L and R in Table III, in (a) and (b). Figure 12 depicts the Δ RDT against the RSNR for babble and factory noises, for cases L and R, in (c) and (d). Babble noise is used for the solid lines, the top axis and the legends while factory noise is used for the dashed lines. Figures 12(a)-(d) show that the Δ RDT improves and the raw

Figure 11. Plot of Δ PESQ against RSNR for: (a), (b) white noise, and (c), (d) babble noise (solid lines) and factory noise (dashed lines). In (a) and (c), $T_{60} = 0.40$ s and DRR = 0.17 dB (i.e. index L in Table III). In (b) and (d), $T_{60} = 0.73$ s and DRR = -2.1 dB (i.e. index R). In (c) and (d), babble noise is used for the top axis and for the legends.

Figure 12. Plot of Δ RDT against RSNR for: (a), (b) white noise, and (c), (d) babble noise (solid lines) and factory noise (dashed lines). In (a) and (c), $T_{60} = 0.40$ s and DRR = 0.17 dB (i.e. index L in Table III). In (b) and (d), $T_{60} = 0.73$ s and DRR = -2.1 dB (i.e. index R). In (c) and (d), babble noise is used for the top axis and for the legends.

RDT of noisy reverberant speech increases with decreasing RSNR. Also, the Δ RDT scores are better for stationary white noise than for non-stationary factory and babble noises.

Figure 13 shows the Δ PESQ and the Δ RDT against the RSNR, from 5 to 20 dB, for the phase-aware KF algorithm for white, factory and babble noises. Figure 13 examines the acoustic conditions J to V that correspond to the room $10 \times 7 \times 3$ m in Table III. Figure 13 differs from Figs. 11 and 12 in presenting the indexes J to V and not only L and R. According

Figure 13. Plot of (a) Δ PESQ, and (b) Δ RDT against RSNR (dB) for the algorithm for white, factory and babble noises. The indexes J to V are shown.

to Fig. 13(a), the Δ PESQ decreases as the T_{60} increases. The Δ PESQ increases with decreasing RSNR and the Δ PESQ is higher for white noise than for factory and babble noises. In Fig. 13(b), the Δ RDT improves as the T_{60} increases for high RSNRs and the Δ RDT improves with decreasing RSNR.

In summary, we have tested the KF algorithm in different noises, RSNRs and acoustic conditions with different T_{60} and DRR. The algorithm is effective in decomposing noisy reverberant speech into speech, reverberation and noise. According to Figs. 7-13, the algorithm achieves a significant performance gain compared to the distorted speech and the baselines.

C. Algorithmic Latency and Computational Complexity

The latency of the phase-aware algorithm is 24 ms due to the AR modelling and the reverberation priors, using the parameters in Sec. IV. Using MATLAB on a laptop equipped with a 2.9 GHz Intel Core i5 processor and parallel computation with 2 cores for processing STFT bins in parallel, the real-time factor from [89] is 35. The complexity is high since s_t , r_t and n_t are estimated along with γ_t and β_t using (23)-(31) and Table II. The computation time is dominated by the calculation of the integrals over u , u' and u'' that use MATLAB's "integral" function. The real-time factor could be substantially reduced if sigma points were used to perform these integrals. The large number of parameters evaluated at every frame makes the real-time implementation of the KF algorithm that models inter-frame correlations more computationally challenging [52].

VI. CONCLUSION

In this paper, we present a non-linear KF algorithm in the log-spectral domain to blindly suppress noise and reverberation while accounting for inter-frame dynamics. The first two moments of the posterior of the speech log-spectrum are estimated in noisy reverberant environments using a model that adaptively updates the reverberation parameters. The algorithm tracks the γ_t and β_t reverberation parameters to further improve speech estimation. We show by means of theoretical and experimental analyses that Kalman filtering can be performed in adverse conditions by performing the signal decompositions into speech, reverberation and noise, propagating backwards through the proposed signal model. Experimental results using instrumental measures show improved performance against the T_{60} and the RSNR compared to the noisy reverberant speech and to alternative competing techniques that perform denoising and dereverberation either in concatenation or jointly.

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