2024 18th International Workshop on Acoustic Signal Enhancement (IWAENC) | 979-8-3503-6185-8/24/$31.00 ©2024 IEEE | DOI: 10.1109/IWAENC61483.2024.10694068

BAYESIAN SOUND FIELD ESTIMATION USING UNCERTAIN DATA

Jesper Brunnström[⋆], *Martin Bo Møller*[†], *Jan Østergaard*[‡] *and Marc Moonen*[⋆]

[⋆]STADIUS Center for Dynamical Systems, Dept. of Electrical Engineering (ESAT), KU Leuven, Leuven, Belgium
[†]Bang & Olufsen, Acoustics R&D, Struer, Denmark
[‡]Dept. of Electronic Systems, Aalborg University, Aalborg, Denmark

ABSTRACT

Accurate sound field estimates are often cumbersome to obtain, since they generally rely on microphone measurements at several spatial positions within a room. In addition, room acoustics are often non-stationary, in which case the sound field has to be repeatedly re-estimated with new measurements. However, since the new and old measurements are recorded in different acoustic environments, it is not straightforward to fully exploit the combined measurements. In this paper, a Bayesian approach is taken where older measured data are considered to be more uncertain than newer data. The proposed method allows for the use of data captured in different acoustic environments. For each set of measurements, the position, directivity, and number of microphones are allowed to differ. It is demonstrated on real sound field measurements that the proposed approach is effective, being able to better account for different levels of uncertainty in the data.

Index Terms— sound field estimation, Bayesian, sequential estimation, Kalman filter

1. INTRODUCTION

Many audio applications, in particular sound field reproduction, require sound field estimates associated with some sound sources to one or more regions in the room. The measurement process is time-consuming and can be costly. The difficulty of the sound field estimation problem is exacerbated by the non-stationarity of the room response over time [1–3]. Causes of such changes include temperature changes, and movement of people or items in the room. Because of this non-stationarity, new measurements are likely required after a period of time, as the previous measurements become inaccurate, reflecting the acoustic environment before it changed. However, there can still be relevant information remaining in the previous measurements, if the new acoustic environment is similar to the previous. Therefore, by making use of previous measurements, the new sound field estimate could be improved.

A sound field can be modelled with a spherical harmonic decomposition, resulting in a countable set of harmonic coefficients representing the sound field [4]. The harmonic coefficients can be estimated through a Bayesian framework [5]. The approach is closely related to methods based on kernel ridge regression [6–9], and Gaussian processes [10]. Although the Bayesian framework has been used in some contexts for sound field estimation [11, 12], exploiting data from different acoustic environments has not been considered. The Bayesian framework is particularly suited to this problem, where the data has different levels of associated uncertainty.

In this paper a temporal model is introduced, considering changes in the underlying sound field between successive measurements. In the considered Bayesian framework, this leads to a Kalman filter like algorithm that can be used to estimate the sound field. The proposed method allows for combining measurements that have been obtained in different acoustic environments. The method allows for microphones of arbitrary directivity, placed in any geometry as long as their positions are known. For each set of measurements, the position, directivity, and number of microphones are allowed to differ. The method is evaluated on real sound field measurements, specifically for room impulse response (RIR) estimation using multiple sets of measurements from same room with different amounts of absorbent materials on the walls. The experiment demonstrates the value of including more data, even in the case where the data is collected from different acoustic environments.

2. PROBLEM STATEMENT

2.1. Sound field model

Consider a simply connected source-free region $\Omega \subset \mathbb{R}^3$. The sound pressure of a sound field u at the angular frequency $\omega \in \mathbb{R}_+$ and position $\boldsymbol{r} \in \Omega$ can be expressed in terms of a spherical harmonic decomposition around the expansion cen-

This research work was carried out at the ESAT Laboratory of KU Leuven, in the frame of Research Council KU Leuven C14-21-0075 "A holistic approach to the design of integrated and distributed digital signal processing algorithms for audio and speech communication devices". This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 956369: 'Service-Oriented Ubiquitous Network-Driven Sound — SOUNDS'. The scientific responsibility is assumed by its authors.

Authorized licensed use limited to: KU Leuven Libraries. Downloaded on January 28,2025 at 14:54:56 UTC from IEEE Xplore. Restrictions apply.

ter $\boldsymbol{r}_c \in \Omega$, defined as

$$u(\boldsymbol{r},\omega) = \sum_{\nu=0}^{\infty}\sum_{\mu=-\nu}^{\nu} \varphi_\nu^\mu(\boldsymbol{r}-\boldsymbol{r}_c,\omega)\alpha_\nu^\mu(\boldsymbol{r}_c,\omega) \quad (1)$$

$$\varphi_\nu^\mu(\boldsymbol{r},\omega) = \sqrt{4\pi} j_\nu\big(\frac{\omega}{c}\|\boldsymbol{r}\|_2\big) Y_\nu^\mu(\hat{\boldsymbol{r}}) \quad (2)$$

in terms of the harmonic coefficients $\alpha_\nu^\mu(\boldsymbol{r}_c,\omega)$, and basis function $\varphi_\nu^\mu(\boldsymbol{r},\omega)$. The basis function is constructed from the spherical Bessel function j_ν of νth order, and the spherical harmonic function Y_ν^μ of order ν and degree μ [4, Definition 3.2]. The speed of sound is c, and $\hat{\boldsymbol{r}}$ is the normalized position vector defined as $\hat{\boldsymbol{r}} = \frac{\boldsymbol{r}}{\|\boldsymbol{r}\|_2}$. With this representation, the harmonic coefficients $\alpha_\nu^\mu(\boldsymbol{r}_c,\omega)$ for all ν,μ can be represented by the infinite sequence of harmonic coefficients $\alpha(\boldsymbol{r}_c,\omega) \in \ell^2(\mathbb{C})$, where $\ell^2(\mathbb{C})$ refers to the Hilbert space of square summable sequences [13, Eq. 6.140]. The inner product of the space is $\langle\alpha,\beta\rangle = \sum_{\nu=0}^{\infty}\sum_{\mu=-\nu}^{\nu}\alpha_\nu^\mu\overline{\beta_\nu^\mu}$ where the overbar denotes complex conjugation. For brevity, ω is omitted from now on.

2.2. Measurement model

Consider M microphones placed at $\mathcal{R} = \{\boldsymbol{r}_1,\boldsymbol{r}_2,\ldots,\boldsymbol{r}_M\}$, such that $\boldsymbol{r}_m \in \Omega$. The microphones are of arbitrary directivity, where the directivity of the mth microphone can be described by the harmonic coefficients $\gamma_m \in \ell^2(\mathbb{C})$ [5]. Note that many common directivities such as omnidirectional, cardioid, and bidirectional, can be represented by only a few nonzero coefficients [7].

The sound recorded by the M microphones can be represented by $\boldsymbol{p} \in \mathbb{C}^M$. A linear measurement operator $\Xi \in \ell^2(\mathbb{C}) \to \mathbb{C}^M$ can be defined explicitly as

$$\Xi(\mathcal{R},\boldsymbol{r}_c)\alpha(\boldsymbol{r}_c) = \begin{bmatrix} \langle T(\boldsymbol{r}_1-\boldsymbol{r}_c)\alpha(\boldsymbol{r}_c),\gamma_1\rangle \\ \vdots \\ \langle T(\boldsymbol{r}_M-\boldsymbol{r}_c)\alpha(\boldsymbol{r}_c),\gamma_M\rangle \end{bmatrix}, \quad (3)$$

where $T(\boldsymbol{r}) : \ell^2(\mathbb{C}) \to \ell^2(\mathbb{C})$ is the translation operator, a linear unitary operator that can be used to translate expansion centers as $\alpha(\boldsymbol{r}) = T(\boldsymbol{r}-\boldsymbol{r}_c)\alpha(\boldsymbol{r}_c)$ [5, Eq. 6]. The complete measurement model is then

$$\boldsymbol{p} = \Xi(\mathcal{R},\boldsymbol{r}_c)\alpha(\boldsymbol{r}_c) + \boldsymbol{\eta}, \quad (4)$$

where $\boldsymbol{\eta} \in \mathbb{C}^M$ is measurement noise. A more detailed explanation of the measurement model can be found in [5].

2.3. Temporal model

Considered a scenario where the sound field is measured on multiple occasions, between which the acoustic environment changes. The sound field for all measurement occasions can then be represented by the sequence of harmonic coefficients $\alpha_b(\boldsymbol{r}_c) \in \ell^2(\mathbb{C})$ for $b \in \mathbb{N}$. There is not necessarily any relationship between the index b and time. For each measurement occasion, the sound field is measured at M_b positions represented by $\mathcal{R}_b$, i.e. not necessarily using the same directivity, positions, or the number of microphones as for other measurement occasions. For measurement occasion b, the data vector is $\boldsymbol{p}_b \in \mathbb{C}^{M_b}$, the measurement noise is $\boldsymbol{\eta}_b \in \mathbb{C}^{M_b}$, and the measurement operator is $\Xi(\mathcal{R}_b,\boldsymbol{r}_c) : \ell^2(\mathbb{C}) \to \mathbb{C}^{M_b}$.

An explicit state-space model can then be introduced, where the harmonic coefficients are considered the state of the system, with a temporal dependence represented by the measurement occasion index b. The temporal model is

$$\begin{aligned} \alpha_b(\boldsymbol{r}_c) &= \alpha_{b-1}(\boldsymbol{r}_c) + w_{b-1} \\ \boldsymbol{p}_b &= \Xi(\mathcal{R}_b,\boldsymbol{r}_c)\alpha_b(\boldsymbol{r}_c) + \boldsymbol{\eta}_b. \end{aligned} \quad (5)$$

The difference in the acoustic environment between two measurement occasions is accounted for by the process noise $w_b \in \ell^2(\mathbb{C})$. The implication of this model is that α_b and α_c are assumed to be more similar for smaller $|b-c|$. The model is constructed with the assumption that minimal knowledge is available about the change in acoustic environment.

3. BAYESIAN INFERENCE

3.1. Probabilistic model

In order to estimate the harmonic coefficients, some assumptions on the probability distributions of the quantities in the model (5) will be made. A circularly symmetric Gaussian distribution on $\ell^2(\mathbb{C})$ can be defined [14], in terms of which the prior distribution of the harmonic coefficients is assumed to be $\rho(\alpha(\boldsymbol{r}_c)) = \mathcal{N}(m_0,C_0)$, for some mean sequence $m_0 \in \ell^2(\mathbb{C})$ and covariance operator $C_0 \in \ell^2(\mathbb{C}) \to \ell^2(\mathbb{C})$. The process noise is distributed as $\rho(w_b) = \mathcal{N}(0,Q_b)$ with the covariance operator $Q_b : \ell^2(\mathbb{C}) \to \ell^2(\mathbb{C})$. The measurement noise is assumed to be distributed according to a known complex circularly symmetric Gaussian distribution $\rho(\boldsymbol{\eta}_b) = \mathcal{N}(0,\boldsymbol{\Sigma}_b)$ where the covariance matrix for measurement occasion b is $\boldsymbol{\Sigma}_b \in \mathbb{C}^{M_b\times M_b}$.

The measurement noise and process noise are assumed to be independent from each other, and temporally white. The sequence of harmonic coefficients is assumed to be Markov, meaning that future harmonic coefficients are independent of past values given the present, defined explicitly as $\rho(\alpha_b|\alpha_{b-1}) = \rho(\alpha_b|\alpha_{b-1},\alpha_{b-2},\ldots,\alpha_0)$ [15, Section 10.1.2].

3.2. State estimation

Based on the probabilistic model, the posterior distribution of the harmonic coefficients for each measurement occasion can be derived in closed form. The resulting updates of the distribution corresponds to a Kalman filter [16, Ch. 13] for

Authorized licensed use limited to: KU Leuven Libraries. Downloaded on January 28,2025 at 14:54:56 UTC from IEEE Xplore. Restrictions apply.

a Hilbert space valued state. The predicted harmonic coefficients before a new measurement has been obtained is $\rho(\alpha_b|\alpha_{b-1}) = \mathcal{N}(m_{b|b-1}, C_{b|b-1})$, for which the mean and covariance is [14, Ch. 1]

$$\begin{aligned} m_{b|b-1} &= m_{b-1} \\ C_{b|b-1} &= C_{b-1} + Q_{b-1}. \end{aligned} \tag{6}$$

The posterior distribution of the harmonic coefficients given the new data $\boldsymbol{p}_b$ is then $\rho(\alpha_b|\alpha_{b-1}, \boldsymbol{p}_b) = \mathcal{N}(m_b, C_b)$, where the mean and covariance is defined as [17, Example 6.23]

$$\begin{aligned} m_b &= m_{b|b-1} + C_{b|b-1}\Xi_b^{\mathsf{H}} P_b(\boldsymbol{p}_b - \Xi_b m_{b|b-1}) \\ C_b &= C_{b|b-1}\Big(I - \Xi_b^{\mathsf{H}} P_b \Xi_b C_{b|b-1}\Big) \\ P_b &= (\Xi_b C_{b|b-1}\Xi_b^{\mathsf{H}} + \boldsymbol{\Sigma}_b)^{-1}, \end{aligned} \tag{7}$$

where Ξ_b is used as shorthand for $\Xi(\mathcal{R}_b, \boldsymbol{r}_c)$. The Hermitian adjoint of the measurement operator $\Xi(\mathcal{R}, \boldsymbol{r}_c)^{\mathsf{H}} : \mathbb{C}^M \to \ell^2(\mathbb{C})$ is defined as

$$\Xi(\mathcal{R}, \boldsymbol{r}_c)^{\mathsf{H}} \boldsymbol{p} = \sum_{m=1}^{M} (\boldsymbol{p})_m T(\boldsymbol{r}_c - \boldsymbol{r}_m)\gamma_m, \tag{8}$$

where $(\boldsymbol{p})_m$ refers to the selection of the mth element.

Using (3) it is possible to express the estimated distribution of the measurements on any set of points $\mathcal{R}$, which is

$$\begin{aligned} &\rho(\Xi(\mathcal{R}, \boldsymbol{r}_c)\alpha_b(\boldsymbol{r}_c)) = \\ &= \mathcal{N}(\Xi(\mathcal{R}, \boldsymbol{r}_c)m_b, \Xi(\mathcal{R}, \boldsymbol{r}_c)C_b\Xi(\mathcal{R}, \boldsymbol{r}_c)^{\mathsf{H}}). \end{aligned} \tag{9}$$

Setting $\gamma_m = \delta_{\nu 0}$, where $(\delta_{\nu 0})_\nu^\mu = 1$ for $\nu = 0$ and zero otherwise, corresponding to an omnidirectional directivity, leads to (9) being a distribution of the sound pressure. The mean of (9) is equivalent to reconstructing the sound pressure from m_b using (1). If needed, the translation operator can be used to move the expansion center $\boldsymbol{r}_c$, affecting the distribution as

$$\rho(T(\boldsymbol{r})\alpha_b(\boldsymbol{r}_c)) = \mathcal{N}(T(\boldsymbol{r})m_b(\boldsymbol{r}_c), T(\boldsymbol{r})C_b T(-\boldsymbol{r})). \tag{10}$$

4. EVALUATION

4.1. Sound field measurements

To demonstrate the properties of the proposed method, it is evaluated on real sound field data. The sound field was captured using a microphone array with 30 omnidirectional microphones, placed on a 6×5 element grid with 10 cm spacing, with all microphones set on the same height in the room. The array was placed in two positions, giving 60 spatial samples of the sound field, shown in Fig. 1. A perfect sweep [18] with a duration of 0.5 s and a maximum frequency of 1000 Hz was used as a loudspeaker signal, averaged over 11 periods to improve the signal-to-noise ratio. The signals were deconvolved by computing the cross-correlation with the loudspeaker signal to produce RIRs, and their discrete Fourier transforms of

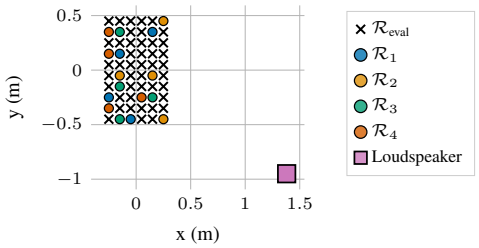


Fig. 1. Positions in the plane for the microphone array and loudspeaker. Each measured point is assigned to a measurement set or the evaluation set.

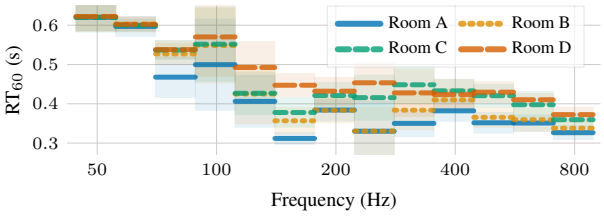


Fig. 2. Reverberation time of room A through D. The solid lines represents the mean, and the shaded regions shows one standard deviation of the RT_{60} over the 60 measured room impulse responses.

length 1000 samples were used as data in the experiment. A few of the highest and lowest frequency bins were excluded, as the signal had insufficient power to make estimation feasible.

The sound field measurements were made using a single loudspeaker in an IEC 268-13 conforming listening room [19]. The room was equipped with acoustically absorbent panels, which could then be removed a few at a time to generate different acoustic environments. RIRs in the same positions were recorded for four different configurations of the absorbent panels, referred to as room A through D, listed from most to least amount of absorbent panels. The reverberation time in terms of the RT_{60} is shown in Fig. 2, computed for third-octave bands by extrapolating from the RT_{30} [20].

4.2. Methods and parameters

The proposed method, referred to as *Kalman*, is compared against two reference methods. The first is *All data*, which is the estimate given by (7) if all data is assumed to be coming from the same measurement occasion, or equivalently the methods given by [5, 6]. *All data* is expected to provide optimal performance when the acoustic environment does not change between measurement occasions. It is also compared against *Only latest data*, which is the same method as *All data*, but only has access to the last measurement set. *Only latest data* provides a baseline against which methods with more data should compare favourably.

Authorized licensed use limited to: KU Leuven Libraries. Downloaded on January 28,2025 at 14:54:56 UTC from IEEE Xplore. Restrictions apply.

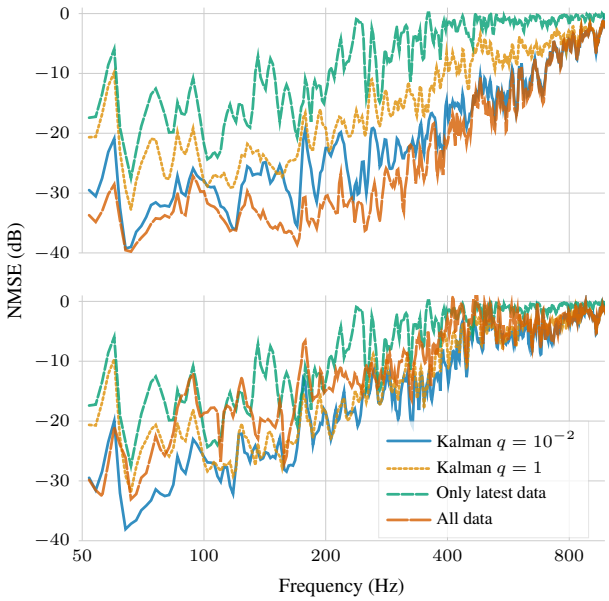


Fig. 3. Mean square error for each frequency, when all data is obtained from room D (top), and when the data is obtained from four different environments (bottom).

For *Kalman*, the process noise covariance is assumed to be of the form $Q_b = qI$, where I is the identity and $q \in \mathbb{R}_+$. Both values $q = 1$ and $q = 10^{-2}$ are considered. It is thereby assumed that the harmonic coefficients are expected to change as much from room A to B as from room B to C and C to D. For general Gaussian distributions as considered here, the number of harmonic coefficients must be restricted to a finite number to be computable. The harmonic coefficients are therefore assumed to be zero for $\nu > 14$, which is above the required order to properly represent the considered sound field, and therefore the exact choice does not affect the results significantly. The required order ν depends on the size of the considered region and the maximum frequency [21].

The measurement noise covariance for all methods is chosen as $\mathbf{\Sigma}_b = \sigma^2 I$, where $\sigma^2 \in \mathbb{R}_+$. The cross-correlation of the loudspeaker signal and the recorded ambient noise reflects the measurement noise contaminating the RIRs, and so is used to calculate σ^2 for each frequency bin. The noise power is similar for all rooms A through D, so the ambient noise recorded in room D is used for all methods and measurement sets. The prior mean and covariance of the harmonic coefficients for all methods is chosen as $m_0 = 0$ and $C_0 = I$.

4.3. Results

The estimation accuracy is evaluated in terms of the normalized mean square error (NMSE), defined as

$$\text{NMSE} = \frac{\|\Xi(\mathcal{R}_{\text{eval}}, \boldsymbol{r}_c)\hat{\alpha}(\boldsymbol{r}_c) - \boldsymbol{p}_{\text{eval}}\|_2^2}{\|\boldsymbol{p}_{\text{eval}}\|_2^2}, \qquad (11)$$

	Same environment	Different environments
Kalman $q = 10^{-2}$	−8.9	**−5.8**
Kalman $q = 1$	−6.6	−5.4
All data	**−9.0**	−4.6
Only latest data	−2.3	−2.3

Table 1. Mean normalized mean square error over all frequencies in decibels, when all data is obtained from room D, and when the data is obtained from four different environments.

where $\hat{\alpha}(\boldsymbol{r}_c)$ is the estimated harmonic coefficients, $\mathcal{R}_{\text{eval}}$ is the evaluation set shown in Fig. 1, and $\boldsymbol{p}_{\text{eval}} \in \mathbb{C}^{46}$ is the associated sound pressure from room D.

Four measurement sets of 4 microphones each were considered, $\mathcal{R}_i$ for $i = 1, 2, 3, 4$, shown in Fig. 1, with the rest being assigned to the evaluation set $\mathcal{R}_{\text{eval}}$. Two scenarios are considered, one where all four measurement sets are from room D, and one where the measurements at $\mathcal{R}_1$ is from room A, $\mathcal{R}_2$ from room B, $\mathcal{R}_3$ from room C, and $\mathcal{R}_4$ from room D. The NMSE as a function of frequency for both scenarios is shown in Fig. 3. The poor performance of *Only latest data* indicates that using the data from only one measurement set is not sufficient, as there are only very few spatial samples. When all measurements are from room D, *All data* performs consistently best. When all measurements are obtained from different environments, both *All data* and *Kalman* perform worse than with data from the same environment. However, the degradation is smallest for *Kalman* with $q = 10^{-2}$, particularly for lower frequencies. A summary of the NMSE is shown in Table 1, indicating that the lowest error given data from different environments is obtained by *Kalman*.

5. CONCLUSION

The problem of sound field estimation using data obtained from different acoustic environments has been considered. The sound field is represented in terms of a sequence of harmonic coefficients, which are estimated using a Bayesian framework, leading to a Kalman filter like algorithm. The method has been evaluated on real sound field data, recorded in the same room with different acoustic conditions. The experiment indicates that the proposed method maintains better sound field estimates when some data was collected in different acoustic environments. In future work, the Bayesian framework will be used for sound field estimation under a more general probabilistic model.

6. REFERENCES

[1] M. Olsen and M. B. Møller, "Sound zones: On the effect of ambient temperature variations in feed-forward

Authorized licensed use limited to: KU Leuven Libraries. Downloaded on January 28,2025 at 14:54:56 UTC from IEEE Xplore. Restrictions apply.

systems," in *Preprints AES Conv.* May 2017, pp. 1009–1018.

[2] M. B. Møller, J. K. Nielsen, E. Fernandez-Grande, and S. K. Olesen, "On the influence of transfer function noise on sound zone control in a room," *IEEE/ACM Trans. Audio, Speech, Lang. Process.*, vol. 27, no. 9, pp. 1405–1418, Sept. 2019.

[3] K. Prawda, S. Schlecht, and V. Välimäki, "Time variance in measured room impulse responses," in *Forum Acusticum*, Sept. 2023.

[4] P. A. Martin, *Multiple Scattering: Interaction of Time-Harmonic Waves with N Obstacles*, vol. 107 of *Encyclopedia of Mathematics and Its Applications*, Cambridge University Press, 2006.

[5] N. Ueno, S. Koyama, and H. Saruwatari, "Sound field recording using distributed microphones based on harmonic analysis of infinite order," *IEEE Signal Process. Lett.*, vol. 25, no. 1, pp. 135–139, Jan. 2018.

[6] N. Ueno, S. Koyama, and H. Saruwatari, "Kernel ridge regression with constraint of Helmholtz equation for sound field interpolation," in *Proc. Int. Workshop Acoust. Signal Enhancement (IWAENC)*. Sept. 2018, pp. 436–440.

[7] N. Ueno, S. Koyama, and H. Saruwatari, "Directionally weighted wave field estimation exploiting prior information on source direction," *IEEE Trans. Signal Process.*, vol. 69, pp. 2383–2395, Apr. 2021.

[8] S. Koyama, J. Brunnström, H. Ito, N. Ueno, and H. Saruwatari, "Spatial active noise control based on kernel interpolation of sound field," *IEEE/ACM Trans. Audio, Speech, Lang. Process.*, vol. 29, pp. 3052–3063, Aug. 2021.

[9] J. G. C. Ribeiro, S. Koyama, and H. Saruwatari, "Kernel interpolation of acoustic transfer functions with adaptive kernel for directed and residual reverberations," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, June 2023.

[10] D. Caviedes-Nozal, N. A. B. Riis, F. M. Heuchel, J. Brunskog, P. Gerstoft, and E. Fernandez-Grande, "Gaussian processes for sound field reconstruction," *J. Acoust. Soc. Am.*, vol. 149, no. 2, pp. 1107–1119, Feb. 2021.

[11] J. M. Schmid, E. Fernandez-Grande, M. Hahmann, C. Gurbuz, M. Eser, and S. Marburg, "Spatial reconstruction of the sound field in a room in the modal frequency range using Bayesian inference," *J. Acoust. Soc. Am.*, vol. 150, no. 6, pp. 4385–4394, Dec. 2021.

[12] D. Caviedes-Nozal and E. Fernandez-Grande, "Spatio-temporal bayesian regression for room impulse response reconstruction with spherical waves," *IEEE/ACM Trans. Audio Speech Lang. Process.*, vol. 31, pp. 3263–3277, 2023.

[13] E. G. Williams and J. A. Mann, *Fourier Acoustics: Sound Radiation and Nearfield Acoustical Holography*, vol. 108, Academic Press, 1999.

[14] G. Da Prato, *An Introduction to Infinite-Dimensional Analysis*, Springer, 2006.

[15] K. P. Murphy, *Machine Learning: A Probabilistic Perspective*, The MIT press, 2012.

[16] S. M. Kay, *Fundamentals of Statistical Signal Processing*, Prentice Hall Signal Processing Series. Pearson, 1993.

[17] A. M. Stuart, "Inverse problems: A Bayesian perspective," *Acta Numerica*, vol. 19, pp. 451–559, May 2010.

[18] C. Antweiler, A. Telle, P. Vary, and G. Enzner, "Perfect-sweep NLMS for time-variant acoustic system identification," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Mar. 2012, pp. 517–520.

[19] IEC TR 60268-13, "Sound system equipment - Part 13: Listening tests on loudspeakers," 1998, [Online]. Available: https://webstore.iec.ch/publication/1213.

[20] R. Scheibler, E. Bezzam, and I. Dokmanić, "Pyroomacoustics: A Python package for audio room simulations and array processing algorithms," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Apr. 2018, pp. 351–355.

[21] R. A. Kennedy, P. Sadeghi, T. D. Abhayapala, and H. M. Jones, "Intrinsic limits of dimensionality and richness in random multipath fields," *IEEE Trans. Signal Process.*, vol. 55, no. 6, pp. 2542–2556, June 2007.

Authorized licensed use limited to: KU Leuven Libraries. Downloaded on January 28,2025 at 14:54:56 UTC from IEEE Xplore. Restrictions apply.