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A robust super-resolution approach with sparsity constraint in acoustic imaging

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ABSTRACT

Acoustic imaging is a standard technique for mapping acoustic source powers and positions from limited observations on microphone sensors, which often causes an ill-conditioned inverse problem. In this article, we firstly improve the forward model of acoustic power propagation by considering background noises at the sensor array, and the propagation uncertainty caused by wind tunnel effects. We then propose a robust super-resolution approach via sparsity constraint for acoustic imaging in strong background noises. The sparsity parameter is adaptively derived from the sparse distribution of source powers. The proposed approach can jointly reconstruct source powers and positions, as well as the background noise power. Our approach is compared with the conventional beamforming, deconvolution and sparse regularization methods by simulated, wind tunnel data and hybrid data respectively. It is feasible to apply the proposed approach for effectively mapping monopole sources in wind tunnel tests.

1. Introduction

Acoustic imaging is widely used for acoustic source power reconstruction and localization. It can provide the useful insights into acoustic performance, acoustic comfort and machinery security in automobile and aeronautic industries for wind tunnel tests [1–4]. In this article, we mainly focus on the signal processing techniques applied in acoustic imaging, such as the Conventional BeamForming (CBF), deconvolution and regularization methods. The CBF method [5] is a direct, robust and rough estimation of source powers and positions, since its spatial resolution is limited due to the high side-lobes. The MUltiple SIgnal Classification (MUSIC) [6] can greatly improve the CBF resolution, but original MUSIC requires the high signal-to-noise ration (SNR) or the exact number of sources to make the subspace separation. Besides, the MUSIC could not directly reconstruct source powers due to its pseudo-power optimization. Based on the CBF, the acoustic power propagation can be modeled by a determined linear system of equations, which could hardly be solved by direct inversions due to the invertible propagation matrix. Therefore, the deconvolution methods, like the CLEAN [7], can iteratively extract strong sources from the blurry beamforming powers. But the CLEAN could leave out weak sources interfered by strong background noises; and some important parameters of CLEAN have to be empirically selected for good performance. Recently, the Deconvolution Approach for Mapping of Acoustic Source (DAMAS) [8] has become a breakthrough and been effectively applied in acoustic imaging for wind tunnel tests by the NASA. The DAMAS can iteratively solve the acoustic power propagation model under the non-negative constraint on source power variables. But the dominant drawback of the DAMAS is the sensitivity to background noises. So that the Diagonal Removal (DR)-DAMAS [8] has been proposed for the noise suppression; however, weak sources could be also removed off by the DR-DAMAS. To overcome the deconvolution drawbacks, the DAMAS with sparsity constraint (SC-DAMAS) [9] can greatly improve the spatial resolution and improve the robustness, but SC-DAMAS could cause overweening effects due to the sparsity parameter selection. The Covariance Matrix Fitting (CMF) method [10] can effectively improve the robustness by jointly estimating the source power covariance matrix and background noise power; however, the original CMF is not feasible to use because of its huge dimensionality of variables in covariance matrix. For robust acoustic imaging, the Spectral Estimation Method (SEM) and its extensions [11,12] are proposed to subtract the reference noise power from the measured data; and this reference noise power can be obtained beforehand by measuring the observed signals without any object in wind tunnel. However, the estimated noise power might be different from the case where the object is installed in the wind tunnel. Furthermore, sparse regularization methods [13–15] have been widely developed by using the ℓ_1-norm. However, some of

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them have to carefully select the regularization parameter, or make necessary approximations on Singular Value Decomposition (SVD). More recently, the Bayesian inference approaches [16–19] have been investigated and achieve more robust and better acoustic imaging results. However, the Bayesian framework often causes very time-consuming computation costs for real applications.

To summarize, all the above state-of-the-art methods have excellent performance on their own applications, but there is no one-fits-all methods; and most of them suffer one of the following drawbacks: coarse spatial resolution, sensitivity to background noises and high computational cost. In addition, most of them need to set some important parameters for good performance.

In this article, our main contributions can be: (1) We firstly improve the robust forward propagation model of acoustic power propagation by considering both the background noises at the microphone sensors, and the propagation uncertainty caused by multi-path propagation in the wind tunnel. (2) We jointly estimate source powers and positions, as well as the background noise power. (3) For acoustic imaging with super-resolution, we investigate an adaptive sparsity parameter estimation procedure. (4) Furthermore, its computational cost maintains feasible to use.

This article is organized as follows: Section 2 introduces the forward model of acoustic signal propagation. Then the improved model of acoustic power propagation is proposed in Section 3. The classical methods are presented in Section 4. Our proposed approach is investigated in Section 5. Then method comparisons are shown on simulations in Section 6 and real data in Section 7. To further confirm the effectiveness of proposed approach, Section 8 demonstrates the performance comparisons on the hybrid data, in which, some known synthetic sources are added to the real data. Finally, Section 9 concludes this article.

2. Forward model of acoustic signal propagation

2.1. Assumptions

For acoustic imaging, a source is usually supposed to be an uncorrelated monopole [7–9,11,20–22]. In this article, we use the monopole model in order to simplify the physical process and explicitly build up the acoustic propagation model. To approach real cases, we use the complex source model which is composed of several monopoles forming different spatial patterns. Moreover, we suppose the background noise at the microphone sensor to be Additive Gaussian White Noise (AGWN), mutually independent and identically distributed (i.i.d), and also independent to sources. Sensors are assumed to be omni-directional with unitary gain. Furthermore, complex reverberations are negligible in wind tunnel, but we consider the first order reflection on the ground, as well as the refraction on the interface between the wind flow and common air.

2.2. Acoustic signal propagation

Fig. 1 illustrates the acoustic signal propagation from the source plane to the microphone sensor array in the wind tunnel, where sensors are installed outside the wind flow. We consider M sensors at known positions $\overline{\mathbf{P}} = [\overline{\mathbf{p}}_1, \ldots, \overline{\mathbf{p}}_M]^T$ with $(\cdot)^T$ denotes transpose operator. On the source plane, we suppose K unknown original source signals $\mathbf{s}^* = [s_1^*, \ldots, s_K^*]^T$ at unknown positions $\mathbf{P}^* = [\mathbf{p}_1^*, \ldots, \mathbf{p}_K^*]^T$, where $\mathbf{p}_k^*$ denotes the 3D coordinates of s_k^*. Then we discretize the source plane into N identical grids at known discrete positions $\mathbf{P} = [\mathbf{p}_1, \ldots, \mathbf{p}_N]^T$, where we assume that K original sources sparsely distribute on these grids, supposing $N > M \gg K$ and $\mathbf{P}^* \subset \mathbf{P}$. Finally we get N discrete source signals $\mathbf{s}$ at known positions $\mathbf{P}$ as:

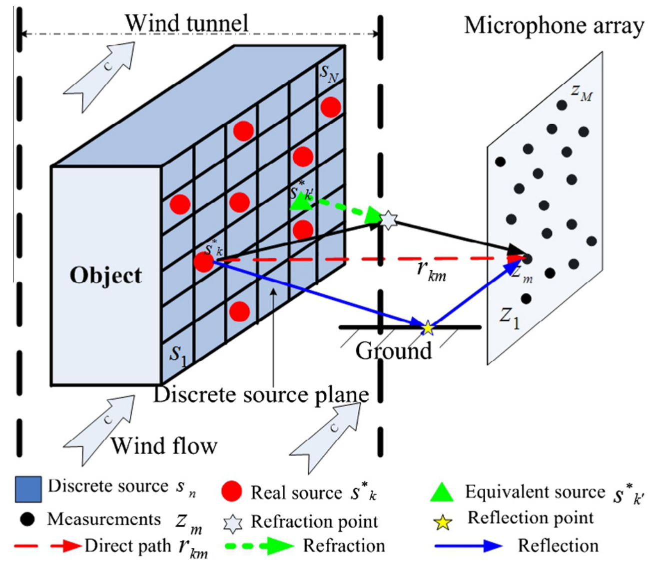

Fig. 1. Illustration of acoustic propagation in the wind tunnel [19].

$$\mathbf{s} = [0, \ldots, s_1^*, 0, \ldots, s_k^*, 0, \ldots, s_K^*, 0, \ldots]_N^T, \tag{1}$$

where $s_k^* = s_n$ for $\mathbf{p}_k^* = \mathbf{p}_n$. Since $K \ll N$, thus $\mathbf{s}$ is a sparse signal with K-sparsity in the spatial domain. Therefore, to reconstruct original source signals $\mathbf{s}^*$ is transferred to reconstruct K-sparsity signals $\mathbf{s}$. To be clear, we state that $\mathbf{s}^* = [s_1^*, \ldots, s_K^*]^T$ denote the original source signals, while $\mathbf{s} = [s_1, \ldots, s_N]^T$ denotes the (discrete) source signals. In Eq. (1), source position $\mathbf{p}_k^*$ can be derived from the position $\mathbf{p}_n$, where the source power of s_n is not 0.

Based on the discrete source model in Eq. (1), we can give the forward model of acoustic signal propagation. For the mth sensor $m \in [1, \ldots, M]$, received signals $\mathbf{z}_{i,m}(t)$ are divided into I sampling blocks with L samplings/block, with sampling block $i \in [1, \ldots, I]$, sampling time $t \in [(i-1)\,L+1, \ldots, i\,L]$ and total samplings $T = I\,L$. Since acoustic signals usually have wide-band frequencies, we apply the L-points Discrete Fourier Transform (DFT) in each sampling block, so that we separate the wide-band into L narrow frequency bins. Since the signal processing is made independently at each frequency bin, we omit the frequency notation f_l, $l \in [1, \ldots, L]$ for simplicity. Finally in the sampling block i, the measured signals $\mathbf{z}_i = [z_{i,1}, \ldots, z_{i,M}]^T$ at M senors can be modeled in the frequency domain as [20]:

$$\mathbf{z}_i = \mathbf{A}(\mathbf{P})\;\mathbf{s}_i + \mathbf{e}_i, \tag{2}$$

where $\mathbf{s}_i = [s_{i,1}, \ldots, s_{i,N}]^T$ denotes N source signals at the ith sampling block. After DFT, $\mathbf{s}_i$ still maintains the sparsity in spatial domain; and $\mathbf{e}_i = [e_{i,1}, \ldots, e_{i,M}]^T$ denotes background noises at M sensors, and we suppose $\mathbf{e}_i \sim \mathcal{N}(0, \sigma^2)$ to be the i.i.d AGWN distribution, where $\sigma^2 = \mathbb{E}[\mathbf{e}_i^H \mathbf{e}_i]$ denotes the noise power, with $\mathbb{E}[\cdot]$ denoting expectation operator and $(\cdot)^H$ conjugate transpose. $M \times N$ complex matrix $\mathbf{A}(\mathbf{P}) = [\mathbf{a}(\mathbf{p}_1), \ldots, \mathbf{a}(\mathbf{p}_N)]$ denotes the signal propagation matrix, where $\mathbf{a}(\mathbf{p}_n)$ denotes the steering vector for the source s_n at the position $\mathbf{p}_n$. As shown in Fig. 1, we can modify the classical definition [20] of $\mathbf{a}(\mathbf{p}_n)$ according to the ground reflection on the ground as follows:

$$\mathbf{a}_n = \mathbf{a}_d(\mathbf{p}_n) + \rho\,\mathbf{a}_r(\mathbf{p}_{-n}), \tag{3}$$

where ρ denotes the reflection coefficient $(0 \leqslant \rho \leqslant 1)$, whose value mainly depends on ground conditions at a given frequency. For the real data used in this article, $\rho = 0.8$ is supposed to be fixed over the frequency band [1600, 2600] Hz in the wind tunnel experiments, thanks to the research contributions of Renault SAS [23].