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Estimation of multiple sound sources with data and model uncertainties using the EM and evidential EM algorithms

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ABSTRACT

This paper considers the problem of identifying multiple sound sources from acoustical measurements obtained by an array of microphones. The problem is solved via maximum likelihood. In particular, an expectation-maximization (EM) approach is used to estimate the sound source locations and strengths, the pressure measured by a microphone being interpreted as a mixture of latent signals emitted by the sources. This work also considers two kinds of uncertainties pervading the sound propagation and measurement process: uncertain microphone locations and uncertain wavenumber. These uncertainties are transposed to the data in the belief functions framework. Then, the source locations and strengths can be estimated using a variant of the EM algorithm, known as the Evidential EM (E2M) algorithm. Eventually, both simulation and real experiments are shown to illustrate the advantage of using the EM in the case without uncertainty and the E2M in the case of uncertain measurement.

1. Introduction

One of the crucial issues in acoustics engineering is to reduce the noise emitted by complex devices, e.g. electric or combustion engines, with a minimum of added mass. The first step of this task is to know and to understand the acoustic behavior of the device in order to focus on the main sound sources and the most annoying frequency bands. Powerful experimental tools for acoustic imaging are able to give a quick overview of the radiation patterns of complex devices. Beamforming [1–6] and Near-field Acoustical Holography (NAH) [7–10] are popular methods dedicated to the aforementioned issue. These approaches are based on pressure measurements obtained from an array of microphones. Beamforming estimates the Direction Of Arrival (DOA) of the plane waves in the farfield case, or the point source location in the near-field case, by maximizing the Delay-and-Sum beamformer, or equivalently by Least Square Estimation (LSE) [1]. In order to cope with the corresponding ill-posed inverse problem, classical Tikhonov regularization can be used to improve the estimation of the source localization [11]. However, beamforming is still restricted due to its limited resolvable source separation in low frequencies and its difficulty to accurately quantify source levels. Alternatively, NAH can be used to backpropagate the sound pressure over a surface near the sound sources. It ensures a higher spatial resolution by taking into account evanescent

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waves and a better quantification by properly solving an inverse problem. Statistically Optimized NAH (SONAH) [8,9] method proceeds similarly but its analytical formalism avoids the errors caused by the use of the discrete spatial Fourier transform in NAH. In a recent paper [12], Antoni presented a unified approach of these different acoustic imaging methods. Based on a Bayesian framework, a super-resolution reconstruction of pressure field is made possible by taking into account prior information about the source distribution. However, all these approaches reconstruct the sound field on a specific surface and thus cannot localize point sources in a 3D space.

This paper proposes a maximum likelihood (ML) approach for the problem of sound source identification in a 3D space. The pressure measured by a microphone is interpreted as a mixture of signals emitted by the various sources. The parameters to estimate are then the locations and strengths of the sources. In the case of a single source, estimating these parameters via ML is straightforward and equivalent to classical beamforming. For multiple sources, however, computing ML estimates of the parameters is difficult, the contributions of the various sources to a measured signal being unknown. Clearly, should these contributions be known, ML estimation would be straightforward as in the single source case. Therefore, Feder and Weinstein [13] proposed to introduce latent variables representing the unknown contributions of the sources to the measured pressures. Then, ML estimates of the model parameters may be obtained via the EM algorithm [14,15]. This algorithm iteratively alternates between two steps: first, the expected source contributions are computed given the current fits of the model parameters; then, these model parameters are updated according to the source contributions newly computed. Similarly, Cirpan and Cikli [16], Kabaoglu et al. [17], Sheng and Hu [18] and Meng et al. [19] investigated the source localization problem using the EM algorithm. However, in all above works, either sound wave attenuation or phase is ignored. In this paper, a more realistic model, where both are considered, is proposed. The sound source estimation problem is then explicitly solved using the EM algorithm.

Contrary to the simulated results presented in the literature, experimental results are always submitted to different kinds of uncertainties [20,21]. In the sound source localization problem, the microphone positions [22–26] and the wavenumber [26–33] in the Green function are never totally certain. Besides, these input parameters can also vary from one measurement to the other, for instance due to motion of the array or to thermal changes. This paper addresses the problem of model estimation from data pervaded by such uncertainties. First and foremost, it should be clear that a distinction is made between randomness and uncertainty. The former stands for irreducible random errors inherent to the environment (such as background and instrumentation noise) and is thus taken into account in the model. The latter corresponds to systematic errors due to an incomplete knowledge of the experimental setting.

Some researchers have investigated how the uncertainties may be taken into account in the sound source localization problem or in other physical models, mainly using propagation of variance [34,35] or error bar [36], probabilistic method [37], Bayesian approaches [38–40,31,41,29,42,43], interval and fuzzy sets analysis [43–46], or belief functions [47,48]. The statistical moment technique coupled with Taylor series expansion [49–51] is frequently used to estimate the output variable uncertainty and some authors [34,35] have used this method to conduct sensitivity and uncertainty analyses in acoustics.

Note that many of the works mentioned above aim at propagating the uncertainty directly through the model. However, sound source estimation is an inverse problem in which imprecise measurements may have a significant impact on the accuracy of the parameter estimates. Some works [31,41,29,38,39] consist in estimating the model in a Bayesian setting by assuming the uncertain parameters as random variables. However, for the case of multiple uncertain parameters and multiple parameters to be estimated, these methods are hardly applicable due to model complexity. Therefore, in order to reduce the model complexity in the uncertainty propagation and parameter estimation, this paper proposes to transfer the uncertainties on some *meta-parameters*[1] of the model, such as microphone locations and wavenumber, to the data level. Then, the resulting uncertain data are used in the estimation process of the model parameters.

The theory of belief functions, also known as Dempster–Shafer theory, is a powerful tool for managing and mining uncertain data. The theory was developed by Dempster and Shafer in Refs. [52–54]. The problem of statistical inference was addressed in Ref. [54] and developed by Denœux [55]. In this latter work, the author proposed a framework in which the data at hand may have been partially or imperfectly observed. Rather than using precise but possibly erroneous data, it is proposed to represent the uncertainty on each measurement using a mathematical tool called contour functions. Then, an extension of the likelihood function and of the EM algorithm, known as the Evidential EM (E2M) algorithm, can be used to maximize the likelihood of such imprecise data. This paper considers uncertainties on some of the meta-parameters such as the temperature of the medium (which has an impact on the wavenumber) and the microphone locations. After the uncertainties on the meta-parameters of the model have been transferred to the data, the E2M algorithm can thus be used to estimate the model parameters.

This article can be seen as a generalization of a previous work [56]. It is organized as follows. Section 2 begins with a description of the model without consideration of uncertainty: the EM algorithm is then used to solve the parameter estimation problem. In particular, the update equations for the model parameters to be estimated (sound source locations and strengths) are provided. Section 3 raises the issue of uncertain measurements, to which the notion of likelihood is extended. Section 4 introduces the E2M algorithm which is used to maximize this generalized likelihood. Section 5 presents experimental results on simulated and real data, with and without taking into account uncertainty. The advantages of the proposed methods are hence demonstrated. Eventually, Section 6 concludes this paper.

[1] By this term, we refer to parameters that are generally considered as known and on which the model implicitly depends.