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Blind Acoustic Source Separation Via System Identification for Leak Detection in Pipelines ⋆

Arne Dankers * **Ehsan Jalilian** ** **David Westwick** *

* *Department of Electrical and Computer Engineering, University of Calgary, Canada (adankers@hifieng.com, dwestwic@ucalgary.ca).*
** *Hifi Engineering Inc., Calgary, Canada (ejalilian@hifieng.com)*

Abstract: The main motivation for this paper is to improve an acoustic leak detection system for pipelines by using blind source separation. In this setup hundreds of microphones are used to continuously monitor a pipeline. We propose to use a source separation scheme to eliminate overlapping sounds in the measured signals making is easier to detect and locate acoustic events in the measured data. To separate the sources, a large scale system identification problem results. In this paper we present one way that the identification problem can be made more computationally efficient. First, the blind source separation problem is parameterized as a channel estimation problem. Due to the presence of echoes, the channel impulse responses are very long, but are sparse in the sense that they are zero for a significant portion of the response. Then this sparsity is exploited for reducing the computational complexity of the identification problem. Our method is tested on a small scale test pipeline.

Keywords: system identification, acoustic blind source separation, leak detection

1. INTRODUCTION

An acoustic measurement is a superposition of multiple acoustic sources that reach a microphone via multiple paths (as illustrated in Fig. 1a). In various applications it is desired to reconstruct the original sources given only the measured signals. This is referred to as *Blind Source Separation* (BSS) and is a well studied topic in the acoustics literature (see Weinstein et al. (1993); Hua et al. (2003); Buchner et al. (2005); Aichner et al. (2006, 2008); Huang et al. (2006a) for instance).

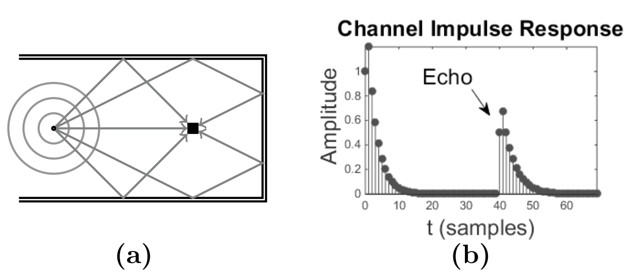

Fig. 1. **(a)** Illustration of sound reflecting in a room. The circle denotes the sound source, the square denotes a microphone, and arrows denote the acoustic paths from source to sensor. **(b)** Example of a channel impulse response with an echo.

In this paper we propose a modification to the typical BSS algorithms in order to obtain a more accurate estimate of the sources and decrease the computation time of the algorithm. We apply the proposed BSS algorithm to a leak detection problem in pipelines. Although there currently exist many adaptive BSS algorithms, implementation of real-time BSS for large scale systems with many measured signals remains a challenge (Huang et al., 2006a,b). In the leak detection setup (presented in detail later in this section) acoustic sensors are spaced evenly along a pipeline, thus for long pipelines there can be a large number of measured signals (possibly hundreds) which is beyond the capacity of current BSS algorithms. We are looking for ways to increase the processing speed of BSS algorithms.
A key observation is that the channel impulse responses in an acoustic system are relatively long due to the presence of echoes. In a pipeline, an echo can be detected 2 or more seconds after the initial sound which is several orders of magnitude longer than the initial response of the system a few milliseconds long. The result is a channel impulse response that is very long, but is zero for most of the time (as shown in Fig. 1b). The channel impulse response is *block-sparse*, meaning that many of the terms in the impulse response are zero, and the non-zero terms appear clustered together in blocks.
In current literature, BSS algorithms do not directly estimate the channel impulse responses, and therefore the sparsity of the channel impulse responses cannot be exploited (Aichner et al., 2008; Huang et al., 2006a). In the first part of this paper we investigate the question: how can the sparsity of the impulse response of an acoustic channel be used in order to obtain faster, more accurate BSS algorithms? There are certainly other ways of increasing the computational speed of BSS algorithms such as using basis functions, or using the interconnection structure of the measurements in relation to the sources, however we will leave these items as future work.

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In the system identification literature and in the channel estimation literature sparse estimation techniques are widely studied. Some examples include *Proportionate Least Squares Estimation* (Helwani, 2015; Paleologu et al., 2010), *LASSO* (Tibshirani, 1994; Rojas et al., 2013), and *Compressed Sensing* (Eldar et al., 2010; Sanandaji et al., 2011). In this paper, we formulate the BSS problem in terms of a channel estimation problem, thereby enabling the potential for using sparse estimation techniques. Then we apply the idea of compressed sensing where only the non-zero parameters are estimated, resulting in a faster and more accurate algorithm since far fewer parameters are estimated. In the next section we will explain how BSS can be used for aiding in leak detection in pipelines.

1.1 Leak detection and localization in pipelines using BSS

Leak detection and localization are relevant issues in today's pipeline industry. Currently in the Canadian province of Alberta there are over 400 000km of oil and gas pipelines and 550 leaks were reported in 2012 (Alberta Energy Regulator, 2013). Monitoring pipelines for leaks is essential for mitigating environmental, health, safety and social risks. Challenges when developing a leak detection system include: obtaining real-time alerts for leaks, achieving the required sensitivity to detect small leaks, achieving accurate estimates of the location of a leak, avoiding false alarms, and developing a cost effective method. There exist a wide variety of methods of leak detection that have been implemented (see Murvay and Silea (2012) and references therein) including methods based on acoustics, pressure or hydrocarbon presence in soil.

The leak detection approach that we are investigating is an acoustic data-driven approach because this approach offers continuous monitoring, is adaptive and uses limited prior knowledge. In addition the deployment of acoustic sensors is more economical than flow rate sensors. The data is collected using acoustic sensors placed along the pipeline as shown in Fig. 2. Acoustic leak detection is an active area of research (see Fuchs and Riehle (1991); Gao et al. (2009); Brennan et al. (2007); Yang et al. (2008); Meng et al. (2012); Qingqing et al. (2013); Wei et al. (2013) for instance). Sources of sound around a pipeline include: sound generated by flow inside the pipe, compressors, generators, rain, wind, rivers, animals, traffic, etc. and leaks in the pipeline. The majority of acoustic leak detection and localization methods are based on estimating the time delay between two measured signals and inferring the location of the leak using the estimated delay and the speed of sound in the fluid of the pipeline Gao et al. (2009); Brennan et al. (2007); Meng et al. (2012). The time delay is estimated using cross-correlation or a variant thereof. These methods are not robust to other noises occurring around the pipe, sound propagating through pipeline walls and surrounding soil, and echoes/reflections of the sound. We propose a leak detection and localization method based on acoustic BSS. There are two main features that distinguish measured signals and source signals: (1) whereas a sound near a pipeline will be present in many of the measured signals, the sound will only be present in one source signal and (2) in the measured signal a reflected sound can appear as a new sound, but in a source signal there are no reflections present. Because of these features determining the presence and location of acoustic events is easier using

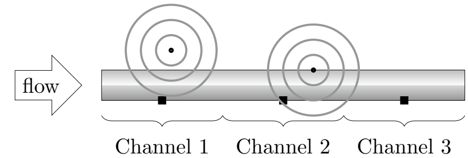

Fig. 2. Diagram of a pipeline and data acquisition setup investigated in this paper. Black squares denote microphones. Acoustic sources are denoted using circles.

source signals (rather than measured signals). Thus we propose to continuously estimate the source signals along a pipeline (using a BSS scheme) and monitor them for changes. Using this approach acoustic events occurring along a pipeline can be detected and localized. However, the event is not categorized. To determine if a detected event is a leak, the event must be further analyzed. Event categorization will not be discussed in this paper.

The pipeline and sensor set up of Fig. 2 can be described by the following assumptions.

Assumption 1. The acoustics satisfy the conditions:

(a) A source i consists of a summation of all sounds originating in channel i.
(b) The acoustic sources occur in, on or near the pipeline.
(c) The sources can be considered stationary for time intervals of a minute or less.
(d) Sound travels through various media including the fluid in the pipe, the pipe wall, and material surrounding the pipeline.
(e) Sound is reflected by valves, imperfections, etc. in the pipe, and interfaces in material surrounding the pipe.
(f) Leaks are not always present, but when they occur they resemble a broadband stochastic process.
(g) The sensors are not be tuned very often (frequency response of the sensors may change).

In the remainder of this paper we present a BSS algorithm that can handle the situation represented by these assumptions, then we apply the method to data collected from a simple pipeline test setup.

2. BLIND SOURCE SEPARATION

First we present the BSS framework (for more details see Makino et al. (2007); Huang et al. (2006a); Aichner et al. (2008)). Then we choose a specific algorithm tailored to the conditions of Assumption 1. Assume that there are the same number of sources as measurements (Assumption 1a), then the measured signals $w_1, \ldots, w_L$ can be assumed to be generated by the *data generating system*:

$$\begin{bmatrix} w_1(t) \\ \vdots \\ w_L(t) \end{bmatrix} = \begin{bmatrix} H^0_{11}(q) & \cdots & H^0_{1L}(q) \\ \vdots & \ddots & \vdots \\ H^0_{L1}(q) & \cdots & H^0_{LL}(q) \end{bmatrix} \begin{bmatrix} e_1(t) \\ \vdots \\ e_L(t) \end{bmatrix}, \qquad (1)$$

where H^0_{ij} are discrete time transfer functions, q^{-1} is the backward shift operator (i.e. $q^{-1}u(t) = u(t-1)$), and $e_1, \ldots, e_L$ are the (unknown) *sources*. The fundamental, enabling assumption that underlies any BSS algorithm is that the sources $e_1, \ldots, e_L$ are mutually independent (Huang et al., 2006a). Equation (1) can be expressed as:

$$w(t) = H^0(q)e(t)$$