2014 IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP)

SEISMIC SIGNAL PROCESSING: SOME RECENT ADVANCES

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ABSTRACT

The goal of this work is to provide a brief overview of some recent advances in the field of seismic signal processing. In particular, we shall focus on tasks such as multiple attenuation and coherent noise elimination, paying special attention to the application of signal separation methods that are able to take into account prior information such as sparsity, which is ubiquitous in reflection seismic. In addition, we briefly review the application of signal transforms, such as wavelets and curvelets, to process seismic data. This article introduces the special session "Seismic Signal Processing", which covers other applications and methods not discussed here.

***Index Terms*—** Seismic reflection, signal processing, signal separation, wavelets.

1. INTRODUCTION

A fundamental problem in geophysics is to estimate the properties of the Earth's subsurface based on measurements acquired by sensors (geophones or hydrophones) located over the area to be analyzed. Among the different methods to accomplish this task, seismic reflection is the most widespread and has been intensively applied for hydrocarbon exploration and investigation of the Earth's crustal structure [1]. The characterization of the subsurface using seismic reflection techniques is conducted by first generating seismic waves using controlled active sources in the surface, such as a dynamite explosion in land acquisition or an air-gun in marine acquisition. Each realization of these seismic sources is known as a shot. The interaction between the environment under analysis and a seismic wave generates reflections that are recorded at the surface. The recorded wave at a receiver on the surface is known as a trace. Seismic signal processing can thus be defined as a set of tools and methods to extract information about the subsurface from a set of traces.

By sorting the signals acquired by the sensors in a proper configuration, it is possible to obtain an image that brings relevant information on the actual Earth's subsurface. For instance, the image depicted in Figure 1 is an example of common-shot gather (CSG), in which each column corresponds to a seismic trace recorded during the same seismic shot. The abscissa here stands for the position of the sensor relatively to the shot position; such displacement is known as offset. Many important parameters related to the subsurface can be extracted from data gathers like this [1].

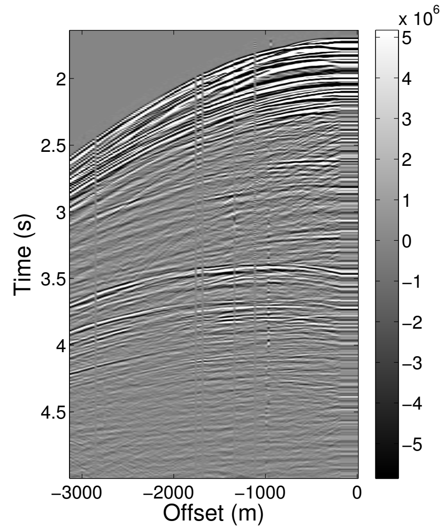

Fig. 1. Example of seismic data arranged in a common-shot gather.

Typically, the Earth's interior has a layered structure, in which each layer has different physical properties. In seismic reflection, one is mostly interested in the waves that propagate in the subsurface and are reflected only once at the interface between the layers, as these reflections carry a direct relationship with the layer structure. These reflections are called primaries, for primary reflections, and are visible in the top part of Figure 1. However, especially in seismic marine acquisitions, seismic waves might bounce several times within the layers, giving rise to the so-called multiple reflections, or simply multiples [2]. Multiple reflections need to be properly attenuated; otherwise they might be mistaken for primaries during the seismic imaging process, which may be a relevant problem for subsequent interpretation by a geologist. In Figure 1, multiples are visible in the bottom part.

In addition to multiples, there are other seismic events that interfere with primary reflections. For example, the emitted seismic wave tends to be diffracted at points along geological faults. While imaging the diffracted waves is paramount to build the final image of the subsurface, these same waves are seen as interferences when performing several seismic processing tasks, since most methods assumed that the data contain only reflections. Another example of seismic wave interfering with reflected waves are surface waves [1]. Surface waves propagate at the interface between the Earth and the air, and do not bring any useful information about the subsurface deeper geological layers. Surface waves are typical of land seismic acquisition, and are characterized by low-frequency components and very high amplitudes. Consequently, unless proper signal processing separation methods are adopted, the reflection events are easily masked by the surface waves.

Classically, the examples of interference mentioned above are attenuated by applying standard transforms, such as Radon and f-k transforms (2D Fourier transform) [2, 3], by using parametric methods [4, 5], or by approaches based on wave propagation modeling [2]. More recently, however, research on the area has been focusing on new tools such as blind source separation (BSS) methods [6, 7]. One interesting aspect concerning the application of BSS to seismic reflection data is that problems in this area are very often unsupervised [8], i.e. there are no reference signals, which matches well with the BSS formulation. Another approach that has been intensively studied is the application of multiresolution transforms such as wavelets and curvelets [9].

In view of these interesting perspectives, the motivation of this paper is to provide a brief overview on the application of BSS and more recent transforms to relevant problems found in seismic reflection. Another goal of this work is to point out that, besides being an exciting field of application to BSS methods and novel transforms, seismic signal processing may also be a tough, and thus inspiring, environment for such paradigms. It is worth mentioning that our study is by no means exhaustive; there are other interesting seismic signal processing methods that will not be discussed in this article. Some examples are the subjects of the invited papers to the special session “Seismic Signal Processing”.

2. SOURCE SEPARATION PROBLEMS

In BSS, the goal is to estimate a set of source signals based only on mixed versions of these sources. Usually, the mixing system is described by an instantaneous and linear model [7]. Moreover, there are generally only two sources and two mixtures in seismic reflection separation problems. In this situation, the mixtures $x_1(n)$ and $x_2(n)$ are given by:

$$\begin{aligned} x_1(n) &= \quad a_{11}s_1(n) + a_{12}s_2(n) \\ x_2(n) &= \quad a_{21}s_1(n) + a_{22}s_2(n), \end{aligned} \tag{1}$$

where $s_1(n)$ and $s_2(n)$ correspond to the sources and a_{ij} to the mixing coefficients. The most employed solution to the BSS problem is based on independent component analysis (ICA) [7], in which the sources are assumed to be mutually statistically independent. Since the sources' independence property is lost after the mixing system, ICA basically searches for linear combinations of $x_1(n)$ and $x_2(n)$ that provide source estimations that are as independent as possible. Such a procedure leads to source separation when there is at most one Gaussian source [10].

The origins of both BSS and ICA date back to the 1980's with the seminal work of Hérault, Jutten and Ans [11]. However, a curious aspect is that the BSS problem was also sketched in a paper published in the geophysical community. In 1984, Harlan, Clarebout and Rocca [12], while dealing with a signal/noise separation problem, proposed a solution that bears strong resemblance to the well-known ICA approach based on non-Gaussianity maximization [13]. In the following, we shall present three examples of source separation problem that can benefit from the advances achieved within the BSS theory.

2.1. Multiple attenuation

An important type of multiple reflection is characterized by a bounce at the acquisition surface. As this is the interface between the subsurface and the air, the reflection coefficient of this bounce is close to one, thus causing a high-amplitude multiple. These surface-related multiples, which are typical of marine acquisitions, can be suppressed by using the surface-related mutiple elimination (SRME) methods [2]. In short, this method comprises two steps. In the first one (the prediction step), the goal is to predict the multiples that are present in the traces. Then, in a second step (the subtraction step), one estimates a matching filter to remove the contribution of the multiple predictions from the acquired data. Typically, a minimum-mean squared error (MMSE) approach is adopted to adjust the matched filter [2].

More recently, the subtraction step of the SMRE was carried out by BSS [14–16]. In this approach, the sources $s_1(n)$ and $s_2(n)$ are given by the primary and multiple reflections, respectively. The mixtures $x_1(n)$ and $x_2(n)$ correspond to the acquired data and the predicted multiples provided in the prediction step — since this prediction is not perfect, it comprises a mixtures of primaries and multiples.

The application of ICA [13] to multiple elimination provided better results with respect to the classical MMSE solution, especially when primaries and multiples cross each other [14]. A recent work has shown that the results provided by a BSS approach can be further improved by taking into account the fact that the primaries can be modeled as a sparse source [17]. Moreover, the results may be further improved if one considers a better modeling for the mixing process taking place in this application. Indeed, although previous works assumed linear instantaneous models, the mixing process here clearly presents dynamical elements which in turn suggests considering convolutive mixing models [18].

2.2. Separation of reflections and diffractions

As mentioned in the introduction, seismic data contain diffractions and reflections of the seismic waves. Both carry valuable information for interpreters; however, they have to go through different types of processing methods, which explains the need to separate diffractions and reflections in seismic data. This is another problem to which blind source separation can be successfully applied. The BSS formulation in this case is straighforward: the sources $s_1(n)$ and $s_2(n)$ are given by the reflections and diffractions, respectively. The mixtures can be obtained after stacking[1]. For instance, the Common-Reflection-Surface (CRS) [19] stacking method may be used to provide a conventional stacked section in which reflections are enhanced, but also to provide a stacked section mainly composed of diffraction events [20]. These two stacked sections present residual diffractions and reflections, respectively, and, thus, can be seen as the mixtures $x_1(n)$ and $x_2(n)$ in a BSS formulation.

In the problem of separating reflections and diffractions, differently from the multiple attenuation problem, the application of BSS based on ICA does not provide good results, being thus necessary to consider prior information other than statistical independence. In [21], a source extraction method based on a sparse criterion provided good separation results both in synthetic and field data.

2.3. Coherent noise elimination

Noise signals that present a particular spatio-temporal structure often arise in reflection seismic data. A typical example is a surface wave known as ground roll [1, 22]. This kind of noise, which is common in land acquisition, is visible in the top part of Figure 2. The depicted data is a CSG after the horizontalization[2] of the primary reflections. Since the ground roll traveltime is different than the traveltime of reflected events, the ground roll is not horizontalized, and it appears as the dipping events in Figure 2, that causes interference with the signal of interest.

A challenge that arises in the separation of ground roll from primaries is that there is only a single mixture in this case: the data itself. Therefore, the classical BSS formulation of (1), which relies on multiplicative models [23], cannot be employed. Instead, the observed data must be described through an additive model, i.e. as a superposition of several components. BSS in additive models can be tackled by established matrix decomposition methods such as the ones based on the singular value decomposition (SVD) [24]. This approach was further developed in [25], where an extension of SVD by incorporating an ICA step was proposed, resulting in a noticeable performance gain in scenarios where there are crossing events. Another extension of SVD was considered in [26]. In these works, the authors have investigated the application of the recently introduced low-ranking modeling methods, such as the robust principal component analysis (RPCA) formulation of [27]. The results obtained so far pointed out that the RPCA can outperform SVD and SVD-ICA in some scenarios, and can provide a compromise in terms of separation quality and computational complexity in other cases.

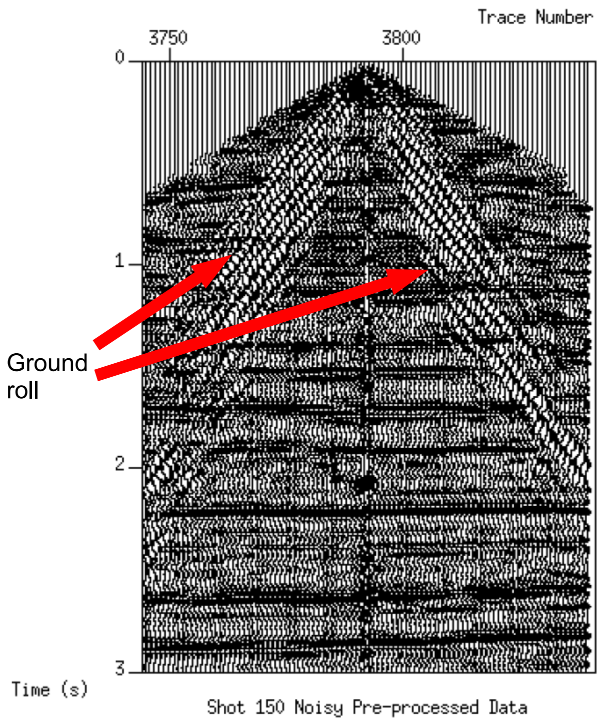

Fig. 2. Example of ground roll.

[1]Stacking is an important step in seismic signal processing and aims at obtaining an improved image in terms of signal-to-noise ratio.

[2]This is done by modeling the time that a reflection takes to leave the source and reach the receiver. With this model, we can correct the data for the differences in traveltime, so that all reflections appear as horizontal events.

3. APPLICATION OF TRANSFORMS

The wavelet transform has an interesting story for the signal processing community, as it is another signal processing tool that, along with linear prediction, for instance, greatly benefited from the rich interplay between digital signal processing in general and seismic signal processing in particular. In fact, the wavelet transform was only proposed in its current form in 1982 [28], due in great part to the work of the geophysicist Jean Morlet, who also coined the term wavelet to describe the functions used in this transform. In this section, we briefly review some successful applications of wavelets to some problems in seismic signal processing.

Perhaps the most important wavelet for seismic processing is the curvelet transform [29]. As for all wavelets, curvelets have local characteristics in the frequency domain. Curvelets, however, are also local in space in a very special way: they are able to approximate boundaries (discontinuities) in the data using locally linear approximations, as its frame is formed by elements that are rotations, translations and dilations of a spatially-local signal. In consequence, curvelets provide a good match for data which contain lines or curves, which is exactly what is present in seismic data.

Wavelets have several features that make them uniquely suited to seismic data processing. Perhaps the most important one is that they allow for very sparse representations of seismic signals. This fact has obvious applications, for instance, in compression [30, 31]: instead of storing the whole seismic data, we can only store the few wavelet coefficients that are able to represent the data with the desired accuracy. Another obvious application is seismic data denoising [32]. In this case, it is assumed that the low-energy wavelet coefficients contain very little signal information, representing mostly the random noise. By ignoring these low-energy components, we are thus to a large extent ignoring noise, while preserving most of the signal information.

In addition to these more traditional applications of wavelets, the knowledge that the wavelet representation of the seismic data *must* be sparse can be exploited for several different ends. (In fact, sparsity is exploited in several applications, and can now be considered a very important aspect of signal processing as a whole [9, 33–36].) One application is the estimation of missing data in the seismic record, such as can happen due to cost-cutting reasons or due to failure of a seismic source or receiver [37]. One example of a seismic record with missing data can be seen in Figure 1, where at least five traces do not contain any data. The method for recovering the signal at the missing spots follows the principles of compressive sampling [33]. The fact that seismic signals have sparse representations in the curvelet domain has also been exploited for the multiple elimination problem [37, 38].

The fact that the wavelet transform yields a sparse representation of the signal has another interesting consequence: the wavelet coefficients extract most of the redundancy present in the data, by combining several redundant parts of the seismic signal into few wavelet coefficients. This observation can be used to estimate some important parameters associated with the seismic data, such as the zero-offset trace [31].

Another important class of problems in seismic signal processing that can benefit from wavelets are the inverse problems [39]. In fact, the final goal of seismic signal processing is an inverse problem: we want to determine a model of the subsurface given some observations acquired at the surface. This is an inverse problem in the sense that, given the model, it is very easy to predict the observations. However, given the observations, it is very hard to determine the model. Representing the model using its wavelet coefficients has been shown to greatly help the solution of the inverse problem (see, e.g., [40]).

4. CONCLUSIONS

The aim of article was to briefly report some recent advances achieved in seismic signal processing. We focused on the application of BSS methods and wavelet-based transforms to relevant problems such as that of multiple attenuation. Of course, due to limited space and to the vast literature in the field, our work is not a comprehensive survey. However, some other topics that are relevant to the field will be covered by the invited papers that will be presented at the special session that is introduced by the present work.

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