ANALYSIS AND SUPPRESSION OF PASSIVE NOISE IN SURFACE MICROSEISMIC DATA

by

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ABSTRACT

Surface microseismic surveys are gaining popularity in monitoring hydraulic fracturing processes. The effectiveness of these surveys, however, is strongly dependent on the signal-to-noise ratio of the acquired data. Cultural and industrial noise generated during hydraulic fracturing operations usually dominate the data, thereby decreasing the effectiveness of using these data in identifying and locating microseismic events. Hence, noise suppression is a critical step in surface microseismic monitoring. In this thesis, I focus on two important aspects in using surface-recorded microseismic seismic data: first, I take advantage of the unwanted surface noise to understand the characteristics of these noise and extract information about the propagation medium from the noise; second, I propose effective techniques to suppress the surface noise while preserving the waveforms that contain information about the source of microseisms.

Automated event identification on passive seismic data using only a few receivers is challenging especially when the record lengths span long durations of time. I introduce an automatic event identification algorithm that is designed specifically for detecting events in passive data acquired with a small number of receivers. I demonstrate that the conventional STA/LTA (Short-term Average/Long-term Average) algorithm is not sufficiently effective in event detection in the common case of low signal-to-noise ratio. With a cross-correlation based method as an extension of the STA/LTA algorithm, even low signal-to-noise events (that were not detectable with conventional STA/LTA) were revealed.

Surface microseismic data contains surface-waves (generated primarily from hydraulic fracturing activities) and body-waves in the form of microseismic events. It is challenging to analyze the surface-waves on the recorded data directly because of the randomness of their source and their unknown source signatures. I use seismic interferometry to extract the surface-wave arrivals. Interferometry is a powerful tool to extract waves (including body-wave and surface-waves) that propagate from any receiver in the array (called a pseudo
source) to the other receivers across the array. Since most of the noise sources in surface microseismic data lie on the surface, seismic interferometry yields pseudo source gathers dominated by surface-wave energy. The dispersive characteristics of these surface-waves are important properties that can be used to extract information necessary for suppressing these waves. I demonstrate the application of interferometry to surface passive data recorded during the hydraulic fracturing operation of a tight gas reservoir and extract the dispersion properties of surface-waves corresponding to a pseudo-shot gather. Comparison of the dispersion characteristics of the surface waves from the pseudo-shot gather with that of an active shot-gather shows interesting similarities and differences. The dispersion character (e.g. velocity change with frequency) of the fundamental mode was observed to have the same behavior for both the active and passive data. However, for the higher mode surface-waves, the dispersion properties are extracted at different frequency ranges.

Conventional noise suppression techniques in passive data are mostly stacking-based that rely on enforcing the amplitude of the signal by stacking the waveforms at the receivers and are unable to preserve the waveforms at the individual receivers necessary for estimating the microseismic source location and source mechanism. Here, I introduce a technique based on the $\tau-p$ transform, that effectively identifies and separates microseismic events from surface-wave noise in the $\tau-p$ domain. This technique is superior to conventional stacking-based noise suppression techniques, because it preserves the waveforms at individual receivers. Application of this methodology to microseismic events with isotropic and double-couple source mechanism, show substantial improvement in the signal-to-noise ratio. Imaging of the processed field data also show improved imaging of the hypocenter location of the microseismic source. In the case of double-couple source mechanism, I suggest two approaches for unifying the polarities at the receivers, a cross-correlation approach and a semblance-based prediction approach. The semblance-based approach is more effective at unifying the polarities, especially for low signal-to-noise ratio data.
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Chapter 1

INTRODUCTION

Low-permeability reservoir rocks such as shales and tight-gas sandstones are commonly stimulated using hydraulic fracturing to increase their permeability and enhance production. In order to maximize productivity, it is critical to distinguish zones that have been affected by hydraulic fracturing from zones that have not. A novel way of identifying these zones is to monitor the seismicity resulting from fracturing and stress changes (Cerda & Alfaro, 2007; Chambers et al., 2010; Eisner et al., 2010; Maxwell & Urbancic, 2001). The magnitude of these hydraulic-fracturing-induced seismic events is mostly less than 1, and they are usually referred to as microseismic events. Imaging of such microseismicity provides valuable information about fracture extent, fracture mechanism, and complexity which ultimately helps in estimating the stimulated reservoir volume and field-development planning. While hydraulic-fracture mapping is the most common application, microseismic monitoring is also conducted for geothermal systems (Romero et al., 1994; Feng & Lees, 1998; Majer et al., 2007), thermal-recovery processes, and reservoir surveillance (Warpinski, 2009).

Numerous considerations go into microseismic monitoring many of which are summarized in Warpinski (2009). They can be broadly categorized into acquisition, processing and interpretation of microseismic data. Important elements of acquisition include positioning of receivers, array design, and choice of sensors. Receivers may be placed close to the treatment wells in boreholes or they may be located on the surface. The above choice is determined by signal strength at the receivers, level of noise, aperture requirements, and economics. The number and location of receivers in an acquisition is also important because noise suppression can be more effective with increasing receivers and thus lead to better imaging of the data. The receivers should also be sensitive to the frequency content of the microseismic energy. According to Warpinski (2009), “The best sensors will be those with high sensitivity and a
flat response over the frequency range of interest.” In post-acquisition, the microseismic data is processed to suppress noise and locate arrivals corresponding to microseisms. Processing also involves recognition of P- and S-wave arrivals, polarization analysis and imaging. In the presence of strong noise, however, processing becomes extremely challenging. To locate microseismic hypocenters, the processed data is imaged using a velocity model. In most cases, the velocity model is obtained from nearby sonic logs or from inversion of surface reflection-seismic data. The quality of the image depends on the signal-to-noise ratio of the data and the accuracy of the velocity model.

Note that the common theme in all the above steps is the effect of noise. Noisy data resulting from poor acquisition or planning can lead to erroneous fracture mapping and will fail to meet the project objectives. Therefore, noise has to be treated at the acquisition stage or at the processing stage before interpretation. In this thesis, I address the noise issue at the processing stage.

Noise presents particularly in surface microseismic data. As mentioned above, monitoring of microseismicity can be done using borehole or surface sensors (Figure 1.1). Although downhole monitoring places sensors close to the treatment well, it provides a limited recording aperture that may impose inaccuracy in microseismic hypocenter imaging and source mechanism estimation (Thornton & Eisner, 2011; Eisner et al., 2010). Surface monitoring in the form of passive data is becoming more common in analyzing the hydraulic fracturing process (Kochnev et al., 2007; Duncan & Eisner, 2010). By passive data, I refer to the continuous recording of ground motion due to uncontrolled sources such as cultural and industrial activities. Because of the potentially larger receiver aperture and higher number of receivers, surface microseismic data may be more informative than downhole data (Eisner et al., 2010; Chambers et al., 2010; Duncan & Eisner, 2010). Yet the effectiveness of this technique is strongly dependent on the signal-to-noise ratio. Cultural and ambient noise usually dominate the data, thereby decreasing the effectiveness of surface microseismic techniques in identifying and locating microseismic events. Hence, noise suppression is a critical step in surface microseismic monitoring (Kochnev et al., 2007; Duncan & Eisner, 2010; Forghani et al., 2012, 2013).
Figure 1.1: a) Plan-view of star-shaped surface microseismic array. The blue lines represent the receiver array and the white lines in the center of the array denote horizontal treatment wells (Source: Duncan & Eisner (2010)). b) Schematic of borehole microseismic acquisition (Source: Warpinski (2009)).
In this thesis, I address the issue of surface noise with two approaches. In the first approach, I exploit the surface-wave noise to extract information necessary for its suppression; in addition, I explore ways in which the noise can also be used for extracting subsurface properties. Under the second approach, I develop techniques that suppress noise while preserving the waveforms of the microseismic events.

The large amount of the surface passive records as well as the low signal-to-noise ratio of these data makes the use of these data challenging. Detection of events becomes especially difficult when only a few receivers are used in the survey. An automated, accurate algorithm is beneficial for event identification when processing days and months of passive data. Moreover, identifying an event in the case of low signal-to-noise ratio, specifically when the acquisition is limited to a few receivers, is challenging. STA/LTA method is a commonly used automatic event identification algorithm which computes the ratio of the short term average (STA) to the long-term average (LTA) of the passive seismic data. This technique has been primarily used to detect earthquakes in global seismology (Ambuter & Solomon, 1974; Chael, 1997; Withers et al., 1998) and later to detect microseismic events in unconventional oil/gas fields (Oye & Roth, 2003; Tan, 2007; Miyazawa et al., 2008a). I show in Chapter 2 that for the case of low signal-to-noise ratio and limited number of receivers, the STA/LTA algorithm is not effective at event identification. Thereafter, I introduce a cross-correlation based technique as an extension of the STA/LTA algorithm. The suggested technique takes advantage of the similarities of the STA/LTA waveforms between receivers and improves the event detectability compared to the STA/LTA algorithm. By providing examples of applying the cross-correlation technique to synthetic data and a field surface passive dataset, I demonstrate the advantage of using this method over the conventional STA/LTA algorithm.

Instead of focusing only on noise suppression, an interesting strategy would be to exploit the noise to infer subsurface properties; also, understanding noise properties might help in their suppression. Therefore, I explore how seismic interferometry can help in extracting surface-noise properties. Although it is commonly thought that both body wave and surface waves can be extracted from interferometry, studies show underestimation of the body waves and dominance of surface waves when applying interferometry to the surface source-receiver
acquisition (Campillo & Paul, 2003; Shapiro & Campillo, 2004; Sabra et al., 2005b; Shapiro et al., 2005; Dong et al., 2006). This issue has created confusion in the applications of the interferometry and has not been clarified in the literature. In Chapter 3 I address this issue and investigate why in surface seismic interferometry mostly surface waves are extracted, while the body waves are not recorded well. The underestimation of the body waves by interferometry can in fact be beneficial for reconstruction/prediction of the surface waves that are mostly considered as unwanted noise in surface seismic data. In order to exploit the extracted surface waves from interferometry, it is important to understand to what extent these waves can be reconstructed. Therefore, I study the feasibility of the reconstruction of surface waves (direct as well as scattered surface waves) by interferometry. This analysis not only clarifies the underestimation of the body waves and limitations to the recovery of surface waves in a unique way, it also provides valuable insight into the understanding of interferometry applications to the surface passive data (as done in Chapter 4).

Apart from the event identification which was the focus of Chapter 2, another challenge of dealing with surface passive records is the presence of surface noise which can mask most of the subsurface arrivals, specifically the weak microseismic events that have traveled from a depth of a few kilometers to the surface. Understanding the surface-wave characteristics can be helpful for suppressing these noise. For example, dispersion characteristics of surface waves reveal the dominant wavelength of these waves which can be used for designing receiver arrays that can suppress part of these waves at the field (Baeten et al., 2000; Draganov et al., 2009). The focus of Chapter 4 is on extracting the surface-wave dispersive characteristics from a passive dataset. In Chapter 3 I show that application of interferometry to surface source-receiver acquisition yields data dominated by surface waves. In Chapter 4, I take advantage of this fact and apply the interferometry to data from surface receivers and sources (industrial noise) to extract the surface waves. Dispersion analysis is then applied to the extracted surface waves from interferometry. I also discuss the application of surface-wave dispersion in understanding the near-surface velocity and surface-wave noise suppression.

The processing and analysis in Chapters 3 and 4, yield sufficient understanding of the surface-wave characteristics and possible ways of suppressing these waves. Conventional
noise suppression techniques in passive data are mostly stacking-based that rely on enforcing the amplitude of the signal by stacking the waveforms at the receivers (Kiselevitch et al., 1991; Kao & Shan, 2004; Kochnev et al., 2007; Duncan & Eisner, 2010). However, waveforms at the individual receivers, which are necessary for estimating microseismic source location and source mechanism (Aki & Richards, 2002) cannot be extracted after processing with such methods.

In Chapters 5 and 6 I propose a noise suppression technique for the surface microseismic data based on transforming the data to the $\tau - p$ domain. While in the time-offset $(t - x)$ domain, the characteristics of microseismic events might not be different from that of surface noise, in the $\tau - p$ domain, they show distinct characters which would help to separate them. With this suggested technique I aim to overcome the challenges in conventional techniques not only in terms of improving the signal-to-noise ratio of the microseismic events, but also preserving the waveforms at the individual receivers. The focus of both chapters is on the noise suppression. While in Chapter 5 I focus on demonstrating the processing and pre-processing steps for the suppression of the noise using simple models, in Chapter 6 I modify the modeling to be more realistic and apply some improvements in the processing steps. For example, the source mechanism considered in Chapters 5 is very simple and does not include the realistic mechanism for which the radiation pattern is defined based on the orientations of a fracture-plane. In Chapters 6, I generate a more realistic microseismic source with the radiation pattern in which the polarities and the amplitude of the recorded waveforms vary with the fracture-plane orientation. In order to unify the polarities for an effective summation of waveforms in the $\tau - p$ transform, in Chapter 5 I apply cross-correlation to identify the polarities of the receivers. However, cross-correlation is not effective when the signal-to-noise ratio is low which is a common case in the surface microseismic data. Therefore, in Chapters 6 I suggest another technique for identifying the polarities, which is based on the semblance analysis. Another additional step different from Chapters 5 is that in Chapters 6 I apply my suggested noise suppression technique to field microseismic data to test its effectiveness on field data.

Most of the results are included in the collections of papers that are presented as chapters
here. The summary of the results is presented in the conclusion chapter.
Chapter 2

AN AUTOMATED CROSS-CORRELATION BASED EVENT DETECTION TECHNIQUE AND ITS APPLICATION TO A SURFACE PASSIVE DATASET

2.1 Abstract

In studies such as heavy oil, shale reservoirs, tight gas, and enhanced geothermal systems, the use of surface passive seismic data to monitor induced microseismicity due to the fluid flow in the subsurface is becoming more common. However, in most studies passive seismic records contain days and months of data and manually analyzing the data can be expensive and inaccurate. Moreover, in the presence of noise, detecting the arrival of weak microseismic events becomes challenging. Hence, the use of an automated, accurate, and computationally fast technique for event detection in passive seismic data is essential.

The conventional automatic event identification algorithm computes a running-window energy ratio of the short-term average to the long-term average of the passive seismic data for each trace. We show that for the common case of low signal-to-noise ratio in surface passive records, the conventional method is not sufficiently effective at event identification. Here, we extend the conventional algorithm by introducing a technique that is based on the cross-correlation of the energy ratios computed by the conventional method. With our technique we can measure the similarities amongst the computed energy ratios at different traces. Our approach is successful at improving the detectability of events with low signal-to-noise ratio that are not detectable with the conventional algorithm. Also, our algorithm has the advantage to identify if an event is common to all stations (a regional event) or to a limited number of stations (a local event). We provide examples of applying our technique to synthetic data and a field surface passive dataset recorded at a geothermal site.
2.2 Introduction

Surface-recorded passive seismic data are being increasingly used for monitoring induced microseismicity resulting from fluid movement and/or stress changes in the subsurface. Recently, such data have become popular for remotely monitoring the hydraulic fracturing processes in oil and gas recovery (Cerda & Alfaro, 2007; Chambers et al., 2010; Duncan & Eisner, 2010; Eisner et al., 2010; Maxwell & Urbancic, 2001), and enhanced geothermal fields (Romero et al., 1994; Feng & Lees, 1998; Majer et al., 2007). A crucial factor in extracting information from passive seismic data is its quality — i.e., the signal-to-noise ratio — so that microseismic events can be correctly identified among the ambient and cultural noise. Also, when analyzing large datasets, the use of an automated algorithm for event identification becomes critical.

One of the commonly used algorithms for automatic event identification which computes the ratio of the short term average (STA) to long-term average (LTA) of the passive seismic data is called $\text{STA/LTA}$. This algorithm has been used to detect earthquakes in global seismology (Ambuter & Solomon, 1974; Chael, 1997; Withers et al., 1998) and later to detect microseismic events in oil fields (Oye & Roth, 2003; Tan, 2007; Miyazawa et al., 2008a). At the beginning of the duration of a recorded event, $\text{STA/LTA}$ ratio increases significantly and at the end of the event this ratio decreases rapidly compared to the rest of the passive signal (Tan, 2007). Hence, this algorithm can be used to identify events characterized by a sudden change in the amplitude.

For the common case of low signal-to-noise ratio, we show that the $\text{STA/LTA}$ algorithm does not perform sufficiently at event identification. We introduce a cross-correlation based technique as an extension of the $\text{STA/LTA}$ algorithm. Our technique detects an event by measuring the similarities of the $\text{STA/LTA}$ energy ratios at the arrival time of the event at receivers. Through examples of applying our technique to synthetic data and a field surface passive dataset, we demonstrate the advantage of using our method over the conventional $\text{STA/LTA}$ algorithm.
2.3 Algorithm

The STA/LTA method is an automatic event-detection technique which computes the energy ratio of the short-term average (STA) to long-term average (LTA) of the passive seismic data using a rolling-window operation. The STA and LTA in the first time window are given by Allen (1978); Tan (2007)

\[ STA = \frac{1}{S} \sum_{j=L-S+1}^{L} a_j^2 \]  

(2.1)

and

\[ LTA = \frac{1}{L} \sum_{j=1}^{L} a_j^2, \]  

(2.2)

respectively. \( L \) and \( S \) are the number of data samples in long-term and short-term windows, respectively, and \( a_j \) is the amplitude of the \( j \)th sample. The \( STA/LTA \) ratio, \( R \), is then estimated by \( R = \frac{STA}{LTA} \). After computing \( R \) in this window, the window is moved by one sample and the \( STA/LTA \) ratio is computed for the new window. For the \( N \)th window, the \( STA \) and \( LTA \) are given by

\[ STA_N = \frac{1}{S} \sum_{j=L-N+1}^{L+N-1} a_j^2 \]  

(2.3)

and

\[ LTA_N = \frac{1}{L} \sum_{j=N}^{L+N-1} a_j^2. \]  

(2.4)

Note that the size of the short-term window \( S \) depends on the duration of the recorded event that needs to be detected. The size of the long-term window \( L \) can be about five to ten times that of the short-term window.

In order to check the accuracy of identifying events by \( STA/LTA \) for the case of low signal-to-noise ratio, we apply this method to a synthetic dataset comprising five traces. In
this data, we assume five receivers located along a line with 500 meters receiver-interval. The synthetic data includes a Ricker wavelet with central frequency of 30 Hz, originating at depth 1.5 km under receiver 1 and arriving at the surface receivers at about 0.5 seconds. The recording is contaminated with Gaussian random noise, such that the average signal-to-noise ratio of the traces is about 1.5. The signal-to-noise ratio is estimated by dividing the root mean square (RMS) amplitude of the signal by that of the noise.

For better clarity, we display the seismograms and the processing results both as wiggles (Figure 2.1) and as images (Figure 2.2). The noise-contaminated seismograms are shown in Figures 2.1(a) and 2.2(a) as wiggles and an image, respectively. Note that we have applied a moveout shift to the seismogram based on the depth of the synthetic event (1.5 km) and using an average subsurface velocity of 3000 m/s. In a real microseismic-monitoring setting, one may use an approximate knowledge about the location of the microseismicity zone and an estimated background velocity field.

We apply the $STA/LTA$ algorithm to each trace of this seismogram. The $STA$ window size is chosen to be 0.01 second (half the duration of the Ricker wavelet) and the $LTA$ window size to be 0.06 second. Figures 2.1(b) and 2.2(b) illustrate the computed $STA/LTA$ values as wiggles and image, respectively. It is evident from these figures that for such low signal-to-noise ratios, when each trace is analyzed independently of the others, $STA/LTA$ algorithm can not properly identify this event.

### 2.3.1 Cumulative cross-correlation

Note that for traces with low signal-to-noise ratio, although the $STA/LTA$ ratio is small, the waveform\(^1\) of this ratio is similar for all the traces irrespective of their individual signal-to-noise ratios. Therefore, when examined together, it is plausible that there is an event at approximately 0.5 sec (Figure 2.1(b)). To clarify the concept of similarity of the waveforms, consider Figure 2.1(b) in which the similarity of the $STA/LTA$ waveforms at the time of the event amongst the receivers is clearly evident.

\(^1\)Note that we define the waveform of the $STA/LTA$ ratios as the change of the amplitude of these ratios with respect to the recorded time of the signal
Figure 2.1: a) Seismogram of a synthetic microseismic event recorded at five receivers at about 0.5 seconds; b) Computed $STA/LTA$ ratio of the seismogram in Figure 2.1(a); c) Summation of the local cross-correlation coefficients for the $STA/LTA$ ratios of Figure 2.1(b).
In order to quantify the similarity/dissimilarity amongst waveforms as a function of time, we adopt a localized cross-correlation approach. Under the time-localized cross-correlation approach, we compute the similarity of the $STA/LTA$ of a trace at a particular time with the $STA/LTA$ of the rest of the traces at the same time using cross-correlation. We estimate the summation of the cross-correlation coefficients for the $j$th sample of the $i$th $STA/LTA$ trace, $C_{ij}$, using the following equation:

$$C_{ij} = \sum_{k=1}^{N_T} \max(R_{i,j}^{w} \otimes R_{k,j}^{w}),$$  \hspace{1cm} (2.5)$$

where $N_T$ denotes the total number of traces, $w$ denotes the window size, $\otimes$ represents cross-correlation, and $R_{i,j}^{w}$ and $R_{k,j}^{w}$ are windowed traces taken around the $j$th sample of the $i$th and $k$th $STA/LTA$ waveforms, respectively. The choice of the cross-correlation window length $w$ is determined by the duration of the event on the $STA/LTA$ waveform. For example, for a short-duration recorded event such as a microseismic event with a duration of 0.02 sec, we use a time window of about 0.02 sec for estimating the cross-correlation coefficients; whereas for a long-duration recorded event such as a teleseismic event with a duration of 20 sec, we use a window size of about 20 sec that is large enough to encompass the whole event.

Equation 2.5 can be interpreted as follows: for any given time sample and any given receiver, we cross-correlate the $STA/LTA$ ratio windowed around that sample with the windowed ratios computed at each of the other receivers. The maxima of all the above cross-correlations are stacked to yield the time-varying similarity of the $STA/LTA$ waveform at that sensor with the rest of the waveforms. Once the above operation has been completed for all the sensors for a particular time sample, the window is moved by a minimum of one time sample and the above cross-correlation procedure is repeated.

If an event is recorded at all the receivers, then the cumulative cross-correlation coefficient at the time of the event will be high for any combination of two sensors. On the other hand, a receiver that does not register the event, when cross-correlated with a recording of a receiver that registers the event, would show a low cross-correlation coefficient.
In order to apply our cross-correlation algorithm to the \(STA/LTA\) ratios in Figure 2.1(b), we first take a cross-correlation window size of 0.02 second (comparable to the length of the event in Figure 2.1(b)). The windowed data (\(STA/LTA\) ratios) at receiver 1 are then cross-correlated with those at the rest of the receivers successively to yield 5 cross-correlated signals. The maxima of each of the 5 cross-correlated signals are added to obtain a measure of the cumulative similarity of the \(STA/LTA\) ratios of receiver 1 with the rest of the receivers. The above operation is then carried out for receivers 2 through 5. These results for receiver 1 through 5 for all times are shown as both wiggles and an image in Figures 2.1(c) and 2.2(c), respectively.

Comparing Figures 2.1(b) and 2.1(c), one can see the waveform of the cumulative cross-correlation values at about 0.5 seconds has a higher signal-to-noise ratio than the waveform of the \(STA/LTA\) ratios; clearly, cross-correlation of the \(STA/LTA\) ratios has performed better in recognizing the microseismic event compared to the \(STA/LTA\) method. Moreover, in Figure 2.2(c) we observe that the cumulative correlation coefficients for all the receivers (even the noisy receivers such as receiver 2) at the time of this event are high, implying large similarity amongst the \(STA/LTA\) waveforms at these receivers.

After applying the \(STA/LTA\) and the cross-correlation algorithms to events with different signal-to-noise ratios, we conclude that while the detectability of \(STA/LTA\) breaks down for signal-to-noise ratios less than 2, the detectability of the cross-correlation technique fails for signal-to-noise ratios less than 1. It is also valid to note that the cross-correlation technique can detect only those events that arrive at the receivers almost at the same time, or the events whose approximate moveout character is known; for the latter events one should apply the estimated moveout shift before applying the \(STA/LTA\) and the cross-correlation (as done here).

### 2.3.2 Cross-correlation before or after Short-term Average/Long-term Average?

It is valuable to question the advantage of first computing the \(STA/LTA\) and then applying the cross-correlation to the \(STA/LTA\) waveforms over reversing the order of the
Figure 2.2: a) Seismogram-image of Figure 2.1(a); b) Computed $STA/LTA$ ratios of the seismogram in Figure 2.2(a); c) Summation of the local cross-correlation coefficients in Figure 2.2(b); d) Summation of the local cross-correlation coefficients of the seismogram in Figure 2.2(a); e) Computed $STA/LTA$ ratios of the cross-correlation coefficients in Figure 2.2(d).
two operations. We evaluate this advantage by changing the order of the STA/LTA with cross-correlation in the above example such that we apply our cumulative cross-correlation technique directly to the seismograms.

Figure 2.2(a) shows the image of the seismograms in Figure 2.1(a). Figures 2.2(b) and 2.2(c) illustrate the images of the STA/LTA ratios of the seismogram and the corresponding local cross-correlation coefficients of those STA/LTA ratios, respectively. The direct cross-correlation image of the seismogram of Figure 2.2(a) is shown in Figure 2.2(d). Comparing Figures 2.2(c) (obtained from cross-correlation of STA/LTA waveforms) and 2.2(d) (obtained from direct cross-correlation of the seismogram waveforms) one can see that although both of these techniques have identified the event at about 0.5 second, cross-correlation of STA/LTA waveforms has a higher signal-to-noise ratio than the direct cross-correlation of the seismogram.

We then apply the STA/LTA to the image of the cross-correlations in Figure 2.2(d) and obtain the STA/LTA image in Figure 2.2(e). Comparing the images of the cross-correlation of the STA/LTA waveforms (Figure 2.2(c)) with the images of the STA/LTA of the cross-correlation waveforms (Figure 2.2(e)), it is clear that cross-correlation of the STA/LTA waveforms performs significantly better in identifying this microseismic event. This is because by averaging out the high frequency noise in the waveform, STA/LTA algorithm enhances the coherency of the signal in the individual traces. The cumulative cross-correlation method is, therefore, able to identify the similarities of the coherent event more effectively using the STA/LTA waveforms than the original waveforms. As a result, the application of the STA/LTA to the seismograms followed by the cumulative cross-correlation yields better event identification.

2.4 Application to passive data recorded at a Geothermal site

Next, we apply the STA/LTA and the localized cross-correlation techniques to a surface passive seismic dataset recorded at a geothermal site. Our goal is to test the ability of our algorithm in detection of different types of events such as cultural or local events (which for
The study area is the Mount Princeton geothermal system, located in the Upper Arkansas River Valley in central Colorado. As this geothermal system is a candidate for an enhanced geothermal system, detecting any microseismic activity, if exists, may help to monitor the seismicity prior to development of this geothermal system and help model the expected induced peak seismicity by production (Majer et al., 2007; Kraft et al., 2009). As the depth of a future production well is considered to be 1 km or deeper in the subsurface, in this data we aim to detect the microseismic events with the moveout character corresponding to this depth.

The passive seismic data in this study were recorded at eight three-component stations using two broad-band and six short-period passive seismic sensors, provided by Incorporated Research Institute for Seismology (IRIS). Short-period stations are less sensitive to frequencies under 2Hz, whereas broad-band sensors are more sensitive to frequencies as low as 0.008Hz. Both sensors record frequencies up to the limit that is defined by the sample rate.

The choice of station locations was primarily determined by property use permits, except for three of the short-period stations (CCWSP, CCCSP and CCESP), which were located based on geological features (Figure 2.3). These three stations are at the Chalk Cliff area which is believed to be above the shear zone created by the fault system (Richards et al., 2010), and therefore, might be an area of active microseismicity.

Note that before applying any event identification algorithm to the passive data, the data is bandpass filtered at different frequency ranges that matches the frequency content of the detected event. Moreover, based on the expected location of the event a corresponding moveout shift is applied to the data. In all the examples provided here, we show only the results of the application of our technique to the recordings at the z-component.

In our first example, we apply the \( STA/LTA \) and the cross-correlation techniques to the recordings of a known teleseismic earthquake. Figure 2.4(a) shows the seismogram of the Java earthquake, Indonesia (magnitude 7.0, depth 46 km) occurred at 7:55 a.m. GMT
Figure 2.3: Location of passive seismic sensors at Mt. Princeton geothermal area; station names SP (in blue triangle) and BB (in red triangle), denote the short-period and broadband, respectively.

(1:55 a.m. local time) on September 2nd, 2009, that is bandpassed with the frequency range 1-5 Hz. The window sizes for computing $STA$ and $LTA$ are chosen to be 20 and 100 seconds, respectively. The two arrivals at 2:14 a.m. and 2:18 a.m. are the P- and S-waves, respectively. It can be seen that except station 7, all the stations register this earthquake. This is also clear from both $STA/LTA$ ratios (Figure 2.4(b)) and the summation of the local cross-correlation of these ratios (Figure 2.4(c)). We attribute the high noise level at station 7 to its bad installation; this station is probably not stabilized under the ground properly.

We can observe another event arriving at 2:21 a.m. which seems to be registered only by the three stations 1, 2, and 3. Because both $STA/LTA$ and cross-correlation images show this event is not registered by the other stations, we consider this event to be a local surface event such as a falling rock from the Chalk Cliffs at the vicinity of these three stations (Figure 2.3).

One can observe that for the case of high signal-to-noise ratio as in the Java earthquake, the effectiveness of $STA/LTA$ technique in event identification is comparable to that of the cross-correlation approach. Note that in the case of a local event (such as the event at 2:21 a.m. that is only registered by adjacent stations), because the waveforms are similar only among certain receivers, cross-correlation is unable to detect the event. Nevertheless, we
Figure 2.4: a) Seismogram of the Java earthquake recorded at our stations; traces in this seismogram are normalized with respect to maximum amplitude at each trace. b) $STA/LTA$ ratio computed for the stations showing the earthquake event; c) Summation of the local correlation coefficients of the $STA/LTA$ ratios at the stations.
emphasis that our goal for using the cross-correlation algorithm is to automatically detect events that are common among all the receivers.

Another example of the automatic event identification using the localized cross-correlation approach is shown in Figure 2.5. Figure 2.5(a) illustrates the seismogram of a half an hour time interval of the passive data recorded on September 23, 2009. Note that the seismogram is bandpass filtered within the frequency range of 10-20 Hz. Figure 2.5(b) shows the $STA/LTA$ ratio estimated for these traces, in which the window sizes for computing $STA$ and $LTA$ are chosen to be 5 and 30 seconds, respectively. The large $STA/LTA$ ratio at about 3:54 a.m. on sensors 1 to 5, corresponds to the event which can also be seen on the seismograms in Figure 2.5(a) marked by the red dashed rectangle. To the naked eye (in Figure 2.5(a)), it is not very clear if this event is registered by stations 6 through 8. The low signal-to-noise ratio of the data recorded on the rest of the sensors (6, 7, and 8) makes the event identification, with the $STA/LTA$ algorithm (Figure 2.5(b)), difficult.

We therefore, apply our cross-correlation technique to the $STA/LTA$ ratios, which is shown in Figure 2.5(c). The advantage and robustness of the localized cross-correlation approach is clearly visible by comparing Figure 2.5(c) with Figure 2.5(b). It is unclear from the $STA/LTA$ ratio (Figure 2.5(b)) whether this event is registered by stations 6, 7 and 8. The local cross-correlation, however, shows that this event is registered by stations 6 and 8 but not by station 7. Hence, in a case that the signal-to-noise ratio is low (less than 2), the localized cross-correlation approach is more successful than the $STA/LTA$ in event identification.

Nevertheless, distinguishing the precise arrival time (first break) of the event using the cross-correlation approach is a drawback of this technique. For example, in Figure 2.5(b), the $STA/LTA$ ratio detects the peak arrival time of the event (beginning of the red area) to be at 3:54 a.m.; on the other hand, in Figure 2.5(c), because of a wider window in the cross-correlation image, this arrival time is detected about 30 seconds earlier. The underlying reason for the low resolution of the cross-correlation method is that the moving-window cross-correlation smears the event. In addition, the cross-correlation method is the result of two averaging processes in a certain window length – one averaging the amplitudes to compute
Figure 2.5: a) Seismogram of an event recorded at the eight stations at time 3:54 a.m., on September 23rd, 2009; traces in this seismogram are normalized with respect to maximum amplitude at each trace. b) Computed $STA/LTA$ ratio of the seismogram in Figure 2.5(a); c) Summation of the local cross-correlation coefficients for the $STA/LTA$ ratios of Figure 2.5(b).
the $STA/LTA$ ratios and the other, averaging the maximum cross-correlation coefficients that result in low resolution. Note that as the purpose of using cross-correlation technique is only automatic event detection in a certain time window, this drawback of cross-correlation may not be problematic. Once an event has been detected, the interpreter can look closely at the seismograms to ascertain the exact arrival time and waveform of the event. However, when the arrival times of two or a group of events that have similar moveout characteristics are very close to each other, cross-correlation technique may fail in recognizing the time difference and may detect those events as a single event.

It is valid to mention, in order to use the cross-correlation algorithm to detect a microseismic event, we first need to apply an approximate moveout shift to the recorded seismograms at the stations. Here we estimate the moveout shift for each sensor based on the distance of the sensor from the expected depth of a microseismic event (1 km) under the shear-zone (Chalk Cliffs) area. Our algorithm did not detect any microseismic activity on the moveout corrected data. Possible explanations for the non-detecting any microseismic event could be that the restricted area that we consider for the location of the microseismic events is not naturally active in microseismicity, or the microseismic activity exists but is extremely weak that is under the detection threshold that can be detected by our algorithm. Note that we are only interested in the microseismic events that demonstrate the moveout characteristics corresponding to the location of the future production well at depth 1 km under the Chalk Cliffs area. However, there might exist active microseismic zones at other locations in the subsurface that are not the focus of our investigation.

2.5 Conclusion

In this work, we demonstrated that the conventional $STA/LTA$ algorithm, is not sufficiently effective in event detection in the common case of low signal-to-noise ratio. It also does not exploit the fact that the same event is recorded on multiple receivers. We introduced an extension of the $STA/LTA$ algorithm that looks for local similarities in the $STA/LTA$ ratios amongst different receivers. Our algorithm has the advantage of identifying events
common to all receivers. The cross-correlation method has successfully revealed the low signal-to-noise event that was not detectable with \textit{STA/LTA}.

One of the drawbacks of the cross-correlation algorithm is that it requires an approximate knowledge of the moveout character for an event which needs to be detected. The estimated moveout time shifts should be applied to the recorded waveforms prior to conducting the \textit{STA/LTA} and the cross-correlation. Moreover, because of an extra averaging in calculation of the cumulative cross-correlation coefficients, the accuracy of this technique for identifying the exact arrival time of an event is less than the \textit{STA/LTA} method.

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Chapter 3

UNDERESTIMATION OF BODY WAVES AND FEASIBILITY OF SURFACE WAVE RECONSTRUCTION BY SEISMIC INTERFEROMETRY

3.1 Abstract

It is commonly thought that both body wave and surface-wave parts of the Green’s function can be reconstructed by interferometry. This is, however, not true in practice since the accuracy of the retrieved Green’s function is restricted by the limited distribution of the sources. In fact, studies on applying interferometry, for the case where both sources and receivers are on the surface, have shown that the extracted body waves are extremely weak. In this paper, we analyze the reasons for the underestimation of the body waves extracted by interferometry, when sources and receivers are at the surface. The underestimation of the body waves in seismic interferometry can potentially be used for ground-roll suppression. Conventional ground-roll suppression methods such as f-k filtering become less accurate as these waves get scattered by near-surface heterogeneity. Therefore, we study the feasibility of the scattered surface wave reconstruction by interferometry.

3.2 Introduction

Interferometry is a technique to extract the Green’s function between two receivers as if one of the receivers acts as a virtual source (Snieder, 2004; Wapenaar, 2004; Bakulin & Calvert, 2006; Curtis et al., 2006; Wapenaar & Fokkema, 2006). The interferometry method has been applied in both crustal and exploration seismology. This method has been applied to the field fluctuations excited by either passive sources (Weaver & Lobkis, 2001; Campillo & Paul, 2003; Draganov et al., 2004; Larose et al., 2005; Sabra et al., 2005a,b; Shapiro et al., 2005; Weaver, 2005; Draganov et al., 2007) or active sources (Bakulin & Calvert,
2004; Hornby & Yu, 2007; Mehta et al., 2007, 2008), in order to extract the Green’s function between each receiver pair.

It is commonly thought that the Green’s function estimates obtained from interferometry accurately represents the full Green’s function, but this is not always the case. In fact, the accuracy of the retrieved Green’s function, which consists of the surface- and body waves, is in practice restricted by the limited distribution of the sources of field fluctuations.

We demonstrate the importance of adequate source distribution for the accuracy of the retrieved Green’s function, using examples from interferometry applications. In these examples, sources are either controlled (such as in exploration seismology) or uncontrolled (such as in crustal seismology). If uncorrelated sources with an equal power spectrum surround the receivers and scatterers on a closed surface (Figure 3.1(a)), the full wave Green’s function between the two receivers can be retrieved (Wapenaar & Fokkema, 2006). In reality, sources may not be present on such a closed surface; the source distribution can be non-uniform and may even show gaps. When part of the closed surface is a free surface (Figure 3.1(b)), no sources are required on that free surface to extract the full-wave Green’s function (Wapenaar & Fokkema, 2006). This is also rarely the case in practice.

Consider a source-receiver distribution where sources are in the interior and receivers are located at the surface of the earth (Figure 3.2(a)). For such a distribution, the reflected body wave between the two receivers can be retrieved. In this case the source in light blue gives the dominant contribution to the extraction of the reflected body wave between the two receivers. In exploration seismology, placing controlled sources under the reflector is usually not feasible. In crustal seismology, however, there are several studies in which body waves are reconstructed from teleseismic data excited by passive sources beneath the earth’s layers (Bostock & Rondenay, 1999; Bostock et al., 2001; Shragge et al., 2001; Rondenay et al., 2001; Bostock, 2004; Baig et al., 2005). A more practical source-receiver distribution in exploration seismology uses controlled sources at the surface and receivers in the interior (Figure 3.2(b)).

Bakulin & Calvert (2004) apply interferometry to real 4D VSP data recorded in a well, using controlled shots above the well. They obtain a P-wave image superior to that obtained
Figure 3.1: a) Sources (stars) on a closed surface needed to reconstruct the full-wave Green’s function between the two receivers (triangles) in a 2-D medium, b) sources needed to reconstruct the full-wave Green’s function when part of the closed surface is a free surface. Note that both a) and b) are side views of the distribution.

Figure 3.2: Illustration of two types of source-receiver distributions where, a) receivers are at the surface, sources are beneath the reflector; b) sources are at surface, receivers are in the interior. Note that sources in light blue have the largest contribution to the reconstruction of the reflected body wave between the two receivers.
from surface seismic data. Another example of using sources at the surface and receivers in the interior is shown by Mehta et al. (2007, 2008), who apply cross-correlation interferometry to Mars Ocean Bottom Cable (OBC) data. Using controlled shots near the ocean surface and receivers at the bottom of the ocean, Mehta et al. (2007, 2008) obtain the body-wave Green’s functions. Also, Hornby & Yu (2007) and Vasconcelos et al. (2008a) apply the interferometry method to the data recorded in wells from sources at the surface and use the extracted body waves to image the sub-salt structures.

The question is what happens when both sources and receivers are at the surface? This distribution is of special interest because it is the most common case in both exploration and crustal seismology. For example, ambient seismic noise generated by traffic or wind or ocean waves can be used to probe the earth’s subsurface by interferometry (Shapiro & Campillo, 2004; Sabra et al., 2005a; Stehly et al., 2006; Halliday et al., 2008). Another example of sources and receivers distributed at the surface is USArray, where ambient sources and receivers are at the surface. Applying correlation interferometry to USArray data is an approach to illuminate the subsurface between each deployed station pair. Seismic interferometry has been particularly useful in extraction the surface-wave properties when applied to USArray (Shapiro et al., 2005; Gerstoft et al., 2006; Moschetti et al., 2007; Lin et al., 2008). In all studies where sources and receivers are distributed at the surface, an important question regarding the application of interferometry still remains: Can the body waves be satisfactorily extracted by interferometry? Several studies show extracted body waves in this case to be extremely weak (Campillo & Paul, 2003; Shapiro & Campillo, 2004; Sabra et al., 2005b; Shapiro et al., 2005; Dong et al., 2006), although Roux et al. (2005) and Draganov et al. (2006, 2007, 2009) identify weak body waves as well as the surface waves between two stations when applying interferometry to ambient seismic noise.

In the following section, we identify the reasons for underestimation of the body waves by interferometry in the case that sources and receivers are located at the surface. We can actually use the underestimation of the body waves for reconstruction of the surface waves by interferometry. The reconstructed surface waves can be used for ground-roll suppression in exploration seismology or velocity tomography in both shallow geophysics and crustal
seismology. In order to use the extracted surface waves in these applications, it is important to understand to what extent surface waves can be reconstructed by interferometry. Therefore, in the application section, we study the feasibility of the reconstruction of surface waves (direct as well as scattered surface waves) by applying interferometry to two synthetic data sets. The first dataset is from a 2-D medium in which surface waves propagate along a 1-D scattering path and the second data is from a 3-D medium in which surface waves propagate in a 2-D scattering plane. Our synthetic modeling shows that the main factors for the reconstruction of the surface waves are the source aperture and the azimuth of the inter-receiver line.

3.3 Analysis

In this study, we provide synthetic examples which are based on a 2-layer model in a 2-D medium (Figure 3.3).

In the following we present the reasons for the under-representation of the body-waves Green’s function by interferometry when both sources and receivers are at the surface.

3.3.1 Limited number of stationary source locations for body wave

Regardless of the source location shown in Figure 3.4(a), cross-correlation of the surface-wave recordings at receivers A and B gives an event with a travel time that corresponds to the surface wave propagating between A and B (dashed arrow). Therefore, every source location along the source receiver line on either side of the two receivers contributes to the
reconstruction of the surface wave that propagates between the two receivers. For sources located between the receivers, however, cross-correlation does not yield the surface-wave event between A and B.

In contrast to the surface wave extraction, only specific sources contribute to the retrieval of the body wave propagating between the two receivers. For example, among all the sources shown in Figure 3.4(b), source $S$ contributes most to the extraction of the reflected body wave along the raypath $AMB$. This source, $S$ is called *stationary source* for the reflected body waves. All the other sources in dark blue in Figure 3.4(b) have a smaller contribution to the reconstruction of the body waves, and are called *non-stationary sources*.

Cross-correlation of the two receiver waveforms from stationary sources gives the correct arrival time for the reflected body waves between the two receivers. However, cross-correlation from non-stationary sources gives an arrival time that does not correspond to the arrival time of the reflected body wave, such an arrival does not correspond to any physical arrival and is called a *non-physical* arrival (Snieder et al., 2008). It is common in exploration and crustal seismology that very few, or no sources are present at the stationary locations.

Let us look at a synthetic example to see what happens to the body-wave amplitude if we average the cross-correlations over stationary and non-stationary source locations. One stationary and one non-stationary source are shown in Figures 3.5(a) and 3.5(b), respectively.
The corresponding cross-correlations of their waveforms at receivers A and B are shown in the top and middle panel of Figure 3.5(c), respectively. For illustration purposes, we have corrected the amplitude loss of the receiver waveforms for geometrical spreading and a small reflection coefficient. We can see in Figure 3.5(a) that the time difference of the primary reflection at receiver A and the secondary reflection at receiver B gives the correct arrival time for the reflected body wave that propagates between the two receivers. The first arrival in the top panel of Figure 3.5(c), corresponds to this reflected body wave. The second arrival corresponds to the surface wave propagating between the two receivers.

The time difference of the primary reflection in Figure 3.5(b) at receiver A (dashed line) and the secondary reflection at receiver B (solid line) does not give the correct arrival time for the reflected body wave that propagates between the two receivers. This means that cross-correlation of the two receiver waveforms from a non-stationary source creates a non-physical arrival. This non-physical arrival is the first arrival shown in the middle panel of Figure 3.5(c). The last arrival in this panel corresponds to the surface wave that propagates between the two receivers. The average of the two cross-correlations in the top and middle panels of Figure 3.5(c), is shown in the bottom panel. The surface wave (last arrival in bottom panel) is unchanged by the averaging because of the constructive interference of these waves. In Figure 3.5(c), the grey dashed line points to the correct body-wave arrivals. By following this grey line, we can see the body-wave arrival in the top panel which is reconstructed from the stationary source location; however, there is no arrival for the reflected body wave from the non-stationary source in the middle panel; therefore, in the average of the cross-correlations over the stationary and non-stationary sources, the amplitude of the reflected body wave (second arrival in the bottom panel), is reduced with a factor two. The black dashed line points to the non-physical arrivals in the middle and bottom panels. For this particular example where we average the cross-correlations over two sources, these non-physical arrivals remain. However, we briefly explain in section 4 that the non-physical arrivals vanish by averaging the cross-correlations over an adequate number of sources.
Figure 3.5: a) A stationary and b) a non-stationary source location for the reconstruction of the body waves. c) The top and middle panels are the cross-correlations from the stationary and the non-stationary sources, respectively; the bottom panel is the average of the cross-correlations over stationary and non-stationary sources. The first arrival in the top panel is the body wave and the second arrival is the surface wave propagating between the two receivers. The first arrival in the middle panel is a non-physical arrival that is created by the non-stationary source. The second arrival is the surface wave. In the bottom panel, the first arrival is the non-physical arrival, the second and third arrivals are the body and surface waves, respectively, propagating between the two receivers.
3.3.2 Small reflection coefficients

To analyse the influence of reflection coefficients on the body-wave amplitude, we consider the 2-layer model in Figure 3.3. We focus on cross-correlating the primary reflection at receiver A with the secondary reflection at receiver B, because the cross-correlation of these two creates the primary reflected body wave propagating along $AMB$ between the two receivers. The primary reflection recorded at receiver A has an amplitude proportional to the reflection coefficient $R$, and the secondary reflection recorded at receiver B has an amplitude proportional to $-R^2$. The negative sign denotes the reflection from the free surface with reflection coefficient -1.

Cross-correlating the primary reflection at receiver A with the secondary reflection at receiver B extracts the body wave which kinematically corresponds to the reflected body wave propagating between the two receivers. The amplitude of the reconstructed body wave is proportional to $-R^3$, while the amplitude of the reflected body wave between the two receivers is proportional to $R$. This means that the cross-correlation increases the power of the reflection coefficient and consequently decreases the amplitude of the extracted body wave. To understand how much the body-wave amplitude decreases after cross-correlation, consider the following example. For $R = 0.1$, which is a fairly large reflection coefficient in exploration seismology, the extracted body-wave amplitude is $(0.1)^3 = 0.001$. This is a hundred times less than the true amplitude of the reflected body wave between the two receivers. No wonder that the extracted body wave is weak! For turning waves which have the reflection coefficient $R = 1$, higher powers of this coefficient do not change the amplitude. Therefore, this argument does not apply to turning waves.

3.3.3 Absence of sources under the reflector

In the previous section we discussed the influence of the reflection coefficient on the body-wave amplitude. Snieder et al. (2006) show that adding sources under the reflector can compensate for the amplitude loss of the body wave due to the small reflection coefficients. We summarize their analysis below. As shown in the previous section, for a source at the
Figure 3.6: Sources at the surface and underneath the reflector which give the dominant contribution to the reconstruction of the reflected body wave between the two receivers. $\rho$ and $\rho_b$ are the densities of the upper and lower layers, respectively; $c$ is the velocity of the two layers.

surface such as $S_1$ in Figure 3.6, the amplitude of the reconstructed body wave between the two receivers is proportional to $-R^3$. On the other hand, the amplitude of the transmitted wave from a source under the reflector such as $S_2$ to receiver A is proportional to the transmission coefficient $T$, while the amplitude at receiver B is proportional to $-TR$. Therefore, the amplitude of the reconstructed body wave from cross-correlating the two receiver waveforms for source $S_2$ is proportional to $-RT^2$.

In addition to the dependence on the reflection and transmission coefficients, the reconstructed body-wave Green’s functions from the sources $S_1$ and $S_2$ are also proportional to the medium densities above and below the reflector, $\rho$ and $\rho_b$, respectively. Summing the cross-correlations from the two sources $S_1$ and $S_2$ yields the reconstructed body wave $G$ with the following dependence on $R$ and $T$:

$$G \propto -(\rho R^3 + \rho_b RT^2).$$  \hspace{1cm} (3.1)

Reflection and transmission coefficients for an interface between two layers of equal velocity are given by $R = (\rho_b - \rho)/(\rho_b + \rho)$ and $T = 2\rho/(\rho_b + \rho)$. Substituting these coefficients into equation 3.1 yields

$$G \propto -\rho R.$$  \hspace{1cm} (3.2)
The same procedure can be performed for two layers of different velocities that for simplicity is not shown here. The Green's function in equation 3.2 is proportional to $R$, which is equal to that of the primary reflection between the two receivers. Equation 3.2 confirms that having sources under the reflector as well as at the surface compensates for the amplitude loss of the body wave caused by a small reflection coefficient. The dominant contribution to the reconstruction of the reflected body wave, $G$, comes from the two sources $S_1$ and $S_2$ (Figure 3.6). Therefore, the absence of sources under the reflector, a common scenario in crustal seismology with shallow sources as well as in exploration seismology, is another reason for the weak body-wave amplitude extracted by cross-correlation.

### 3.3.4 body waves are weak

Geometrical spreading and small reflection coefficients affect the amplitude of the reflected body waves more than the surface waves. This is because of the different propagation paths from source to receiver for these two kind of waves. Therefore, the recorded reflected body waves are weak compared to the surface waves. The seismogram from the Indonesian earthquake in Figure 3.7, provides an example that the recorded body waves are weak compared to the surface waves.

To understand what happens to the amplitude of the body waves after cross-correlation we illustrate the simplified cross-correlation equation for two waveforms $U_A$ and $U_B$ recorded at receivers A and B in Figure 3.3, respectively. These waveforms include both the surface wave and reflected body waves. The surface- and reflected body waves at receiver A are denoted by $S_A$ and $B_{RA}$, respectively, with a similar notation for receiver B. Therefore, the waveforms at receivers A and B can be written as:

$$U_A = S_A + B_{RA}$$

(3.3)
Figure 3.7: Z-component seismogram for the 2004 Northern Sumatra earthquake (magnitude 9) recorded at KIEV (Kiev Ukraine), demonstrating the amplitude ratio of the body to surface wave (Courtesy IRIS).

and

$$U_B = S_B + B_{RB}.$$  \hspace{1cm} (3.4)

Cross-correlating the two waveforms $U_A$ and $U_B$, which is denoted by $C_{AB}$, corresponds, in the frequency domain, to

$$C_{AB} = S_B S_A^* + B_{RB} S_A^* + S_B B_{RA}^* + B_{RB} B_{RA}^*.$$  \hspace{1cm} (3.5)

In this equation, the first term denotes the cross-correlation of the surface wave at receiver A with the surface wave at receiver B and gives the surface wave that propagates between the two receivers. Likewise, the last term, which denotes the cross-correlation of the body wave at receiver A with the body wave at receiver B, is the body wave that propagates between the two receivers. The second and third terms denote the cross-correlation of the body waves with the surface waves and are called cross-terms (Snieder, 2004). These cross-terms do not correspond to any physical arrival. They are also called non-physical or spurious arrivals.

Equation 3.5 provides a reason for the weak amplitude of the extracted body-wave
Green’s function. For most cases, the amplitude of the recorded body wave is substantially smaller than the recorded surface-wave amplitude (Figure 3.7). After cross-correlation, the amplitude ratio of the body to surface wave is even lower. For example, assume that the amplitude ratio of the body to surface wave in the above equation, $|B_{RA}/S_A|$ or $|B_{RB}/S_B|$, is 0.1, which according to the example in Figure 3.7 is a reasonable value. After cross-correlation of the two receiver waveforms, the ratio of the body- to surface-wave terms in equation 3.5, $|B_{RB}B_{RA}^*/S_BS_A^*|$, is 0.01! That explains why the body-wave amplitude is much weaker after cross-correlation. Snieder et al. (2006) in their appendix A for general media prove that the amplitude loss of the body wave after cross-correlation, which is related to geometrical spreading, can be recovered by the integration over the stationary source region. However, the recovery of the correct geometrical spreading does not occur in practical situations, where the source distribution near the stationary locations is inadequate.

In equation 3.5, the amplitude of cross-terms $|B_{RB}S_A^*|$ and $|S_BS_{RA}^*|$ dominates the amplitude of the body wave. In seismic acquisition for an inadequate source distribution, these cross-terms dominate the body-wave amplitude. These terms, however, integrate to zero by summing over an adequate number of sources (Snieder et al., 2006).

The synthetic example in Figure 3.8 shows the cause for the weak reconstructed body waves by equation 3.5. Panels (a) and (b) show the waveforms at receivers A and B, respectively, recorded from source S in Figure 3.3. The arrivals denoted by $B_{RA}$, $S_A$, $B_{RB}$ and $S_B$ are the terms in equations 3.3 and 3.4, which are described above. Panel (c) shows the cross-correlation of the waveforms in the panels (a) and (b) according to equation 3.5. In Figures 3.8a and 3.8b, the recorded amplitude ratio of the body to surface wave ($|B_{RA}/S_A|$ or $|B_{RB}/S_B|$) is approximately equal to 1/2, for illustration purposes. After cross-correlation of the two receiver waveforms, this ratio ($|B_{RB}B_{RA}^*/S_BS_A^*|$) is about 1/4 (Figure 3.8c). Note that because we only use one source, the amplitude of the cross-terms ($|B_{RB}S_A^*|$ and $|S_BS_{RA}^*|$) is larger than the amplitude of the body wave. When comparing the phase of the body-wave arrivals $B_{RA}$ and $B_{RB}$ in Figures 3.8a and 3.8b with the phase of the arrival reconstructed by cross-correlation ($B_{RB}B_{RA}^*$ in Figure 3.8c), we notice that there is a change in phase between these arrivals. This change occurs because in our example only one source contributes to the
cross-correlation. Integration over sources at the stationary region, however, yields a phase shift $\pi/4$, which accounts for the phase of the body waves (Snieder et al., 2006).

### 3.4 Application

When sources and receivers are at the surface, the body waves extracted by interferometry are extremely weak and thus the surface waves are dominant. This underestimation of the body waves extracted by interferometry can therefore be used for surface-wave isolation. These reconstructed surface waves can be used for velocity tomography. Velocity tomography methods use the extracted Green’s function to invert for the velocity model in crustal seismology (Shapiro et al., 2005; Moschetti et al., 2007; Lin et al., 2008; Gerstoft et al., 2006) or in near-surface geophysics (Aki, 1957; Louie, 2001; Chávez-Garcia & Luzón, 2005). In these methods, the arrival times for the direct surface waves are used to invert for near-surface velocities. The reconstructed surface waves also can be used in ground-roll suppression. In most land seismic surveys, ground-roll masks the reflections which carry information about
the deeper subsurface. This makes ground-roll suppression an important step in seismic processing. Conventional techniques for ground-roll suppression such as stacking over geophone arrays, polarization methods, and f-k filtering, can be used to suppress the direct surface waves. These techniques are, however, less effective for the suppression of scattered surface waves (Blonk & Herman, 1994; Herman et al., 1999; Fabian et al., 2002; Herman & Perkins, 2006). Recently, interferometry has been used as one alternative for ground-roll suppression (Dong et al., 2006; Halliday et al., 2007, 2008; Vasconcelos et al., 2008b). Interferometry is promising for the removal of the direct surface waves, but its application to the suppression of the scattered surface waves has not been shown.

For this reason, it is important to understand to what extent the scattered surface waves can be reconstructed by interferometry. This will help us determine the reliability of this method over the conventional methods (such as f-k filtering) which are less effective for suppressing the scattered surface waves. In this section we study the feasibility of the surface-wave reconstruction by applying interferometry to the synthetic data from a 3-D scattering medium. In this synthetic model, we do not include the body waves; hence, we focus on the dimensions of the surface-wave propagation paths (2-D). Our modeling is based on single scattering for isotropic point scatterers (Groenenboom & Snieder, 1995). The phase velocity model used for the surface-wave dispersion (Figure 3.9) corresponds to the dispersion curves of Luo et al. (2008).

For a 3-D medium, if sources with an equal power spectrum surround the receivers and the scatterer on all sides (as light and dark blue sources shown in Figure 3.10(a)), both direct and scattered surface waves would be reconstructed. As long as we have sources around the receiver line (shown in Figure 3.10(a) as light blue), direct surface waves can be reconstructed by interferometry. These light blue sources are the stationary sources for the direct surface waves.

The influence of the source aperture on the reconstruction of the direct surface waves in a 3-D medium is illustrated with the following synthetic example. The solid line in the top panel of Figure 3.10(b) shows the waveform reconstructed by averaging the cross-correlations over all sources on the closed surface.
These sources are shown in Figure 3.10(a) as light and dark blue. The waveform shown as a dashed blue line corresponds to the recording at receiver B from a source at receiver A. The first and second arrivals are the direct and scattered surface waves, respectively. Comparing the surface waves reconstructed by cross-correlation with the recorded surface waves, we recognize that interferometry has properly extracted both direct and scattered surface waves. Note what happens when we include only the light blue sources in Figure 3.10(a) in the cross-correlation. The solid line in the bottom panel of Figure 3.10(b) shows the waveform extracted by summing the cross-correlations from these light blue sources. The waveform shown as a dashed blue line corresponds to the recording at receiver B from a source at A. Comparing the surface waves reconstructed by cross-correlation with the recorded surface waves in the bottom panel, we see that the direct surface waves (first arrivals) are properly extracted. However, the second arrivals (shown as a solid line), which are reconstructed by cross-correlation, do not have the correct amplitude and phase of the recorded scattered surface waves. This is because the stationary source region for the direct surface waves differs from that of the scattered surface waves.

For the reconstruction of the scattered surface waves different source positions are
Figure 3.10: a) Plan view of the required sources (shown in light blue) for the reconstruction of the direct surface waves in a 3-D medium; b) reconstruction of both direct and scattered surface waves (the solid line in the top panel) by summing over all the sources on the closed surface; reconstruction of the direct surface waves (solid line in the bottom panel) by summing over sources in light blue. The waveform shown in blue dashed line is the direct recorded Green’s function at one receiver from a source at the other receiver’s location.
needed, depending on the scatterer’s location. For example, for the specific location of the scatterer in Figure 3.11(a), the sources in light blue are needed to reconstruct the scattered surface waves. These light blue sources are the stationary sources for the scattered surface waves.

We illustrate the contribution of the source aperture to the reconstruction of the scattered surface wave via the example in Figure 3.11(b). The solid line in the top panel of this figure shows the reconstructed waveform when we include all the sources on the closed surface in the summation of the cross-correlation. Because we use all sources, both direct and scattered surface waves are well reconstructed compared to the recorded surface waves (the same situation as in Figure 3.10(b)). The solid line in the bottom panel of Figure 3.11(b) shows the waveform extracted by summing the cross-correlations from the light blue sources in Figure 3.11(a). Again, the waveform shown in a dashed blue line corresponds to the recording at receiver B from a source at A. Comparing the surface waves reconstructed by cross-correlation with the recorded surface waves in the bottom panel, we recognize that the scattered surface waves (second arrivals) are properly extracted. However, the first arrival shown as a solid line which is reconstructed by cross-correlation, does not have the correct amplitude and phase of the direct surface waves. This is because the stationary source region for the scattered surface waves differs from that of the direct surface waves.

As we mentioned, the source aperture needed for the reconstruction of the scattered surface waves depends on the location of the scatterer in a medium. Therefore, when the scatterers are everywhere in the medium, for reconstruction of the scattered surface waves, sources with an equal power spectrum are needed everywhere on the closed surface. This is a much more stringent condition than having sources at the stationary region for the direct waves. For this reason, the extraction of scattered surface waves by interferometry is more challenging than the extraction of the direct surface waves only.
Figure 3.11: a) Plan view of the required sources (shown in light blue) for the reconstruction of the scattered surface waves in a 3-D medium; b) reconstruction of both direct and scattered surface waves (the solid line in the top panel) by summing over all the sources on the closed surface; reconstruction of the scattered surface waves (solid line in the bottom panel) by summing over light blue sources. The waveform shown in blue dashed line is the direct recorded Green’s function at one receiver from a source at the other receiver’s location.
3.5 Conclusions

Studies of the extraction of the Green’s function from cross-correlation, when both sources and receivers are at the surface, face a common problem: the under-estimation of the body waves compared to the surface waves. We identified the following causes for this problem using analytical reasoning supported by numerical examples:

1. Theory states that for an ideal source distribution on a closed surface surrounding the receivers with sources of the same power spectrum, the exact Green’s function between the two receivers can be extracted by cross-correlation. The inability to extract the exact Green’s function must therefore be caused by imperfections in the source distribution.

2. For the reconstruction of the direct surface wave, it is sufficient to have a source anywhere along the receiver line as long as it is not located between the receivers. For the reconstruction of the body waves, however, the source must be located at the appropriate stationary phase region. This condition may not be satisfied by natural or cultural passive sources or even by active sources present in a seismic survey.

3. Cross-correlation of body waves excited by the sources located at the surface contains a \textit{product} of reflected waves, which makes their amplitude smaller than the true reflected body waves. Sources at depth can result in a proper reconstruction of the body-wave amplitude; however, since it is uncommon to have controlled sources in the subsurface, the extracted body-wave amplitude remains underestimated.

4. The cross-terms between body waves and surface waves that occur in the cross-correlation for an individual source are much larger than the correlation of the body waves with themselves. These spurious cross-terms between body waves and surface waves integrate to zero when sources are uniformly distributed over a closed surface; but this is not necessarily the case when the distribution of those sources is inhomogeneous.

The underestimation of the body waves from interferometry could potentially be used for surface-wave isolation which in turn is useful for near-surface velocity tomography and
ground-roll suppression. Since conventional ground-roll suppression techniques (such as f-k filtering) are inadequate for the removal of scattered surface waves, interferometry can possibly provide a proper alternative for suppressing these scattered waves. We studied the feasibility of the surface-wave reconstruction by applying interferometry to the data from a scattering medium. Our analysis shows that one can extract the direct surface waves when sources are present along the receiver line. The extraction of the scattered surface waves is more challenging because the extraction of each of these waves requires sources with an equal strength in each stationary phase region of the scatterer involved. This implies that when scattered-waves arrive from all directions, i.e. when scatterers are everywhere, one needs a homogeneous source distribution. This requirement is often not satisfied.

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Chapter 4

DISPERSION ANALYSIS OF PASSIVE SURFACE-WAVE NOISE GENERATED DURING HYDRAULIC-FRACTURING OPERATIONS

4.1 Abstract

Surface-wave dispersion analysis is useful for estimating near-surface shear-wave velocity models, designing receiver arrays, and the suppression of surface waves. Here, we analyze whether passive seismic noise generated during hydraulic-fracturing operations can be used for surface-wave dispersion analysis. Applying seismic interferometry to noise measurements, we extract surface waves by cross-correlating several minutes of passive records; this is distinct from previous studies that used hours or days of passive records for cross-correlation. We also apply dispersion analysis to active-source data recorded by the same receiver array as the passive data. The active and passive data show a good agreement in the dispersive character of the fundamental mode surface-waves. For the higher mode surface waves, however, because of their different frequency content, active and passive data resolve the dispersive properties at different frequency ranges. We invert the observed surface-wave dispersive characteristics for the near-surface shear-wave velocity.

4.2 Introduction

Dispersion is defined as the frequency-dependence of velocities. While body waves show dispersive character primarily due to the presence of intrinsic attenuation, surface waves show dispersion mostly due to near-surface vertical heterogeneity (Dobrin, 1951; Liner, 2012). Low-frequency surface waves penetrate deeper, sample higher velocities, and therefore travel faster. High-frequency surface waves, on the other hand, sense only the shallow near-surface thereby resulting in a low velocity.
Dispersion analysis can provide valuable information for acquisition design and suppression of surface-wave noise, and it can also be used for inverting for near-surface velocity models. The dominant wavelength of surface waves computed from dispersion analysis can be used for designing receiver arrays that suppress these waves (Baeten et al., 2000; Draganov et al., 2009). Dispersive characteristics of surface waves also have long been used to infer shear-wave near-surface velocities, in near-surface geophysics for estimating the building response to ground shaking caused by earthquakes (Borcherdt & Glassmoyer, 1992; Louie, 2001) or in crustal seismology to extract the shear-wave velocity model of the crust and upper mantle (Shapiro & Ritzwoller, 2002; Sabra et al., 2005b).

Moreover, because dispersion is a distinguishable property of surface waves, understanding this property can provide a potential opportunity to suppress these waves. In active seismic data, surface-wave noise suppression techniques are formulated in the frequency-wavenumber (Claerbout, 1985) or frequency-slowness domain (Hampson, 1986) to separate the surface waves from the body waves. For surface microseismic data, however, because of the low signal-to-noise ratio of the body waves generated by microseismic events and the complex nature of surface-wave noise, the suppression of this noise is a significant challenge (Kochnev et al., 2007; Duncan & Eisner, 2010; Forghani et al., 2012, 2013).

Dispersion analysis of passive data is commonly applied to the passive noise generated from cultural activities, mostly road traffic (Halliday et al., 2008; Park et al., 2007). Here, we analyze whether passive energy observed during microseismic monitoring of hydraulic-fracturing operations can be used for surface-wave dispersion analysis.

Studies show that combined active and passive dispersion analysis provides broader frequency content of the dispersive surface waves, thereby resulting in a more complete analysis of these waves (Malovichko et al., 2005; Park et al., 2005; Halliday et al., 2008; Park et al., 2007). For example, the combined active and passive surface-wave analysis by Park et al. (2005) resulted in a better recognition of the surface-wave modes and more accurate estimation of the shear-wave velocity. Malovichko et al. (2005) and Park et al. (2007) used combined active and passive dispersion analysis for better estimation of near-surface soil properties.
Here, we extract dispersive characteristics of surface waves using both active and passive data. Because in our study area there is no information about the true near-surface velocities, we also use the dispersion curves to infer the near-surface shear-wave velocity profile.

4.3 Field data description

The datasets for this research were acquired over a Barnett Shale reservoir in the Greater Dallas area, prior to the start of a hydraulic-fracturing process. The energy observed in the passive data is due to activities such as industrial pumps, engines, and trucks at the well-head area (?). Figure 4.1 illustrates the receiver array used in this acquisition.

The acquisition parameters of these datasets are summarized in Table 4.1. Note that the recording frequency range for the passive data (6-200 Hz) is broader than the one for
the active data (6-30 Hz).

Table 4.1: Survey parameters

<table>
<thead>
<tr>
<th>Sampling Rate</th>
<th>2 ms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency Range (active data)</td>
<td>6-30 Hz</td>
</tr>
<tr>
<td>Frequency Range (passive data)</td>
<td>6-200 Hz</td>
</tr>
<tr>
<td>Number of Receivers (Central array)</td>
<td>1197</td>
</tr>
<tr>
<td>Number of Receivers (Outer array)</td>
<td>3871</td>
</tr>
<tr>
<td>Receiver Interval (Central array)</td>
<td>30 m</td>
</tr>
<tr>
<td>Receiver Interval (Outer array)</td>
<td>60 m</td>
</tr>
<tr>
<td>Receiver Component</td>
<td>Vertical</td>
</tr>
</tbody>
</table>

4.4 Dispersion analysis

Dispersion analysis of surface waves commonly involves transformation of the data from the time-offset domain to the frequency-wavenumber (Gabriels et al., 1987) or frequency-slowness domain (McMechan & Yedlin, 1981; Park et al., 1998, 1999; Xia et al., 2007). In our dispersion analysis we follow the methodology of McMechan & Yedlin (1981) that involves applying two transformations to a common shot-gather. First, we apply the \( \tau - p \) transform (also called slant-stack) to transform the data from the time-offset \( (t - x) \) to the \( \tau - p \) domain, based on the following equation

\[
U(p, \tau) = \int_{-\infty}^{+\infty} U(x, t) \, dx = \int_{-\infty}^{+\infty} U(x, \tau + px) \, dx
\]  

(Claerbout, 1985; Stolt & Weglein, 2012), where \( U(t, x) \) represents a recorded event at each receiver in the \( t - x \) domain as a function of recording time \( t \) and source-receiver offset \( x \); \( U(p, \tau) \) represents the event in the \( \tau - p \) domain as a function of intercept with the time
axis ($\tau$) and the slope or apparent slowness ($p$) of the event. Assuming a certain range of slopes and time-intercepts, this transformation can be obtained by summation of the receiver waveforms at each pair of slope ($p$) and time-intercept ($\tau$). Because dispersion involves the velocities at which different surface-wave frequencies propagate, we convert the data from $\tau - p$ to $\tau - v$ domain, considering $v = 1/p$.

Second, we apply a 1-D temporal Fourier transform to transfer the data from $\tau - v$ to the velocity-frequency ($f - v$) domain. This transformation is described by

$$U(v, \omega) = \int_{-\infty}^{+\infty} e^{i\omega \tau} U(v, \tau) d\tau,$$

where $U(v, \omega)$ represents the data in the velocity-frequency or dispersion domain; $\omega = 2\pi f$ denotes the angular frequency of the data.

### 4.5 Dispersion analysis of active data

To extract surface-wave dispersion properties from the active data, we consider a shot gather recorded from the vibroseis source shown by the black star in Figure 4.1. In order to have a comparable dispersion analysis for active and passive data, we choose the location of the active source to be at the vicinity of the passive source location. Figure 4.2(a) illustrates the active shot gather recorded by the receiver array from this source. The early-arrival events with the smallest slope are possibly refraction events. Note in the shot-gather that the different frequencies of surface wave comprise different arrival times, which demonstrate the dispersive character of this wave.

Figure 4.2(b), shows the transformed data in the $\tau - v$ domain. The high amplitude coherent events between 500 m/s and 1000 m/s, represent the range of the phase velocities for the fundamental mode surface wave. The low amplitude coherent events between 1000 m/s and 2000 m/s may show the range of phase velocities for higher mode surface waves.

Next, we transform the data from the $\tau - v$ domain to the $f - v$ (dispersion) domain. In the dispersion domain (Figure 4.2(c)), we can see that the fundamental mode surface wave has frequency content in the range of 6-30 Hz and that it travels with a phase velocity of 550
m/sec to 850 m/sec. The dispersive characteristics of two higher mode surface waves can also be seen but with weak amplitudes. Note that because of the limited frequency range of the vibroseis sweep (6-30 Hz), the frequency content of the active surface wave is limited to this range.

4.6 Dispersion analysis of passive data

The dispersion analysis technique that we apply to active data requires the data in the time domain to be in the form of a shot gather. Because the source of the passive data is uncontrolled, semi-continuous, industrial noise, we do not have shot gathers as in active data. Therefore, we use passive seismic interferometry to extract pseudo shot gathers from the passive data. In seismic interferometry, cross-correlation of two receiver recordings yields the response between the two receivers with one receiver becoming a pseudo-source (Wapenaar et al., 2010). Passive interferometry has been applied to ambient noise in both crustal (Shapiro et al., 2005; Gerstoft et al., 2006; Bensen et al., 2007) and exploration seismology (Miyazawa et al., 2008b; Draganov et al., 2009).

In passive noise interferometry, the time-domain cross-correlation process is given by

\[ G(x_r, x_s, t_r - t_s) \propto \langle u(x_r, t_r) \ast u(x_s, -t_s) \rangle \]  

(Snieder, 2004; Wapenaar, 2004; Wapenaar et al., 2010), where \( u(x_r, t_r) \) is the recorded waveform at a receiver as a function of the receiver location \( x_r \) and the arrival time \( t_r \) of the waveform at that receiver; \( u(x_s, t_s) \) is the recorded waveform at the pseudo-source as a function of the location of the pseudo-source \( x_s \) and the arrival time \( t_s \) of the event at that receiver; \( G(x_r, x_s, t_r - t_s) \) is the extracted waveform that would be recorded at the receiver location \( x_r \), if there was a source at the receiver location \( x_s \); \( \langle \ldots \rangle \) denotes ensemble time averaging of the cross-correlation and can be estimated by summing over a sufficiently long recording time. The cross-correlation extracts surface-wave arrival times, \( t_r - t_s \), from the pseudo-source to every receiver in the array.

We apply the above cross-correlation method to the passive data recorded at the re-
Figure 4.2: (a) Active shot-gather recorded from the active source location shown by black star in Figure 4.1; the traces are sorted by the distance to the shot, but trace number is not proportional to the distance. Note the fundamental and higher mode surface wave arrivals that are marked with black and white arrows, respectively. (b) $\tau - p$ image of the shot-gather in Figure 4.2(a). (c) Dispersion image of the active data obtained by applying 1-D Fourier transform to Figure 4.2(b).
receivers in the central part of the array (gray area in Figure 4.1). A 2-sec time window of these passive data is shown in Figure 4.3. In order to have a proper comparison with the active dispersion analysis shown above, we choose the pseudo-source to be at the same location as the active source (shown by the black star in Figure 4.1).

In Equation 4.3, each cross-correlation in the ensemble is carried out on time windows spanning over 2-sec of the passive data. The choice of 2-sec windows is based on the estimation of the longest travel time for the surface wave to travel across the receiver array. Because the cross-correlation should be summed over a sufficiently long time, we choose a 300-sec time interval for the summation, that involves summation of 150 time windows each spanning over 2 seconds. Figure 4.4(a) shows the pseudo-shot gather resulting from passive seismic interferometry. In the raw passive data (Figure 4.3), no obvious coherent arrivals are evident. However, after applying interferometry (Figure 4.4(a)) we can observe the extracted surface wave in the pseudo-shot gather.

As is done for active data, we transform the pseudo shot-gather in Figure 4.4(a) to the $\tau - v$ domain shown in Figure 4.4(b). The high amplitude coherent events between 500 m/sec and 1000 m/sec correspond to the fundamental mode passive surface wave. In this velocity range, the similarities between the $\tau - v$ domains of the active and passive data are clearly evident from Figures 4.2(b) and 4.4(b). However, in Figure 4.4(b) we observe high amplitude events within the velocity range 1000-2000 m/sec, which are absent in Figure 4.2(b).
note some low amplitude scattered events at later time-intercepts that possibly correspond
to the cross-term noise created by cross-correlation.

Thereafter, we apply the second transformation to the data – moving from the $\tau - v$
(Figure 4.2(b)) to the $f - v$ domain to obtain the dispersion image of the surface wave
(Figure 4.4(c)). It is noteworthy that by using only a few minutes of passive data in our
dispersion analysis, we are able to extract well resolved surface-wave dispersion curves. This
observation differs from previous passive seismic studies that use hours or even days of
passive data (Halliday et al., 2008; Draganov et al., 2009). We speculate we can use a
shorter time interval because the large number of receivers included in the summation of the
$\tau - p$ transform enhances the coherent surface-wave amplitude.

A comparison of the dispersion image of the passive data (Figure 4.4(c)) with that
of the active data (Figure 4.2(c)) shows that both passive and active data demonstrate
similar dispersive characteristics for the fundamental mode surface wave, although the active
fundamental mode is better resolved. This might be the result of the lower signal-to-noise
ratio in the passive data. For the higher mode surface waves, active data lead to a better
resolution for lower frequencies, while passive data resolve the dispersion better for higher
frequencies. This might be related to the different frequency content of the passive (6-200
Hz) and active (6-30 Hz) data.

The pseudo-source location for the above analysis (black star in Figure 4.1) is chosen
based on the analysis by ? who located the surface noise across the receiver array. To
investigate the importance of the pseudo-source location in this dispersion analysis, next we
choose a pseudo-source far from the noisy location in the array (white star in Figure 4.1).
Figure 4.5(a) shows the corresponding pseudo shot-gather for this pseudo-source. Note that
for this pseudo-source, the surface-wave retrieval is not successful. The reason for this will
be clarified in the discussion section. Also, the $\tau - v$ and $f - v$ images of this pseudo
shot-gather (as shown in Figures 4.5(b) and 4.5(c), respectively) do not extract the surface-
wave dispersive properties, except a small part of the fundamental mode . This observation
shows that in this study the pseudo-source location is critical for a successful passive-seismic
dispersion analysis.
Surface-wave dispersion measurements obtained from active and passive data show markedly different frequency content. Therefore, using the two datasets one can achieve a broader and more resolved dispersive characteristics of the surface waves.

### 4.7 Inversion for shear-wave velocity

To extract the shear-wave velocity models from the dispersion curves, we use the GEOPSY software developed by Wathelet (2005). This software uses a direct search method
Figure 4.5: (a) Pseudo shot-gather obtained by cross-correlation of receivers with the pseudo-source shown by the white star in Figure 4.1. (b) $\tau - v$ image of Figure 4.5(a). (c) Dispersion image of the active data obtained by applying 1-D Fourier transform to Figure 4.5(b).
that is based on the neighborhood algorithm (Sambridge, 1999). The algorithm generates
several thousands of earth models and calculates their corresponding dispersion curves using
the propagator-matrix method for a horizontal multi-layered media (Gilbert & Backus, 1966;
Aki & Richards, 2002). During the generation of the models, misfit values which represent
the distance between the calculated dispersion curves and the observed curves are estimated
(Wathelet, 2005, 2008). The shear-wave velocity models with the minimum misfit values are
then chosen as the acceptable models.

Here, we use the observed dispersion curves that are obtained by our dispersion analysis
(shown in Figure 4.6(a) as black curves) as inputs to the inversion algorithm. Note that these
curves are combined passive and active dispersion curves. Inserting these dispersion curves in
the inversion algorithm, we obtain the shear-wave velocity models as shown in Figure 4.6(b).
The most acceptable models are those with the lowest misfit values (shown in red). The
uncertainty (scattering of the acceptable models) deeper than 55 m increases with depth.
This indicates that due to the lack of dispersion values at low frequencies (< 6 Hz) the
shear-wave velocities are not well constrained by the dispersion curves (Lomax & Snieder,
1994). The predicted (calculated) dispersion curves from the shear-wave velocity models
that are shown in Figure 4.6(a) are in a reasonable agreement with the observed curves.

4.8 Discussion

We showed that the choice of the pseudo-source location in passive dispersion analysis
is important for the successful retrieval of surface waves and their dispersion properties. A
pseudo-source close to the source of the passive noise yielded a good quality shot gather. On
the other hand, when the pseudo-source was chosen to be far away from the passive noise
source, the quality of the pseudo-shot gather decreased substantially. Here we discuss the
reason for this observation.

In interferometry, sources within the stationary phase zones (Fresnel zones) have the
maximum contribution to the retrieval of a signal between two receivers (Snieder, 2004).
In the extraction of the direct surface waves between any given pair of pseudo-source and
Figure 4.6: a) Observed dispersion curves (shown in black) used to invert for shear-wave velocity and predicted dispersion curves with high misfit (green) and low misfit (red) values; b) Acceptable shear-wave velocity models with high misfit (green) and low misfit (red) values.

receiver in a homogeneous medium, these stationary sources lie on or in the vicinity of the line that connects the pseudo-source and the receiver (Snieder, 2004; Snieder et al., 2006). When the pseudo-source is selected near the passive noise sources, the direct surface waves can be extracted by cross-correlation for wide range of receivers in the array as is schematically illustrated in Figure 4.7(a). On the other hand, for a distant pseudo-source, the direct surface waves can be retrieved only for a narrow range of receivers (shown in Figure 4.7(b)). As a result, the dispersion curves are more pronounced and better resolved for pseudo-sources proximal to the passive noise sources than for distant ones.

Surface-wave dispersion might potentially be exploited to separate surface waves from body waves. For example, in the passive dispersion domain (Figure 4.4(c)) surgical removal of the surface-wave dispersion curves and a transformation of the rest of the data back to the time-offset domain, might yield the body waves free from the surface-wave noise. Another approach is to apply a velocity filter to the passive data. Since from the $\tau - v$ domain (Figure 4.4(b)) we can find the range of surface-wave velocities, we apply a $\tau - v$ transform to the passive data excluding the surface-wave velocities. Thereafter, by applying the inverse
Figure 4.7: Schematic of the receiver zone (blue shade) in which surface waves are extracted by interferometry from the passive noise sources in the red ellipse area; the pseudo-source (large black star) is located in (a) close to the noise sources and in (b) far from the noise sources. Black dots indicate the rest of receivers in the array for which surface waves can not be extracted.
\( \tau - v \) transform we might be able to retrieve only the body waves in the time-offset domain. These suggested approaches are under investigation.

Receiver arrays are commonly implemented in onshore active survey designs to suppress surface waves right at the acquisition stage. The array design requires the knowledge of the wavelength of the surface waves that need to be suppressed. Dispersion characteristics of surface waves obtained from passive data yield the range of wavelengths for these waves and thus could potentially be used in designing receiver arrays for an active survey or even subsequent passive surveys.

4.9 Conclusions

Here, we performed a combined active and passive dispersion analysis to extract and analyze the dispersive characteristics of surface waves. The passive data used here was generated from various operations during hydraulic fracturing of a tight gas reservoir. Pseudo-source gathers extracted from the passive data using interferometry were of better quality when the pseudo-source location was close to the passive noise sources.

The dispersion character of the fundamental mode is observed to be the same for both the active and passive data. However, for the higher mode surface waves, passive and active data yield dispersion behaviors at different frequency ranges. Combining the passive and active dispersion analysis, we obtained surface-wave properties within a broader frequency band. We inverted the combined passive and active dispersion curves and obtained a range of acceptable near-surface shear-wave velocity models.

Acknowledgments

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by the U.S. Government.
Chapter 5

NOISE SUPPRESSION IN SURFACE MICROSEISMIC DATA

5.1 Abstract

We introduce a passive noise suppression technique, based on the $\tau-p$ transform. In $\tau-p$ domain, one can separate microseismic events from surface-noise based on distinct characteristics that are not visible in the time-offset domain. By applying the inverse $\tau-p$ transform to the separated microseismic event we suppress the surface-noise in the data. Our technique significantly improves the signal-to-noise ratios of the microseismic events and is superior to existing techniques for passive noise suppression in the sense that it preserves the waveform.

5.2 Introduction

Gas shales have very low permeability; therefore, hydraulic fracturing of these reservoirs can help increase the reservoir permeability and hydrocarbon recovery (Sayers & Calvez, 2010). Passive seismic monitoring is a common tool used to characterize changes in the reservoir due to hydraulic fracturing. Because of typically broader receiver aperture and more spatial coverage, surface passive data can be more informative than downhole data (Duncan, 2005; Kochnev et al., 2007; Eisner et al., 2010; Chambers et al., 2010; Duncan & Eisner, 2010), yet the effectiveness of this surface monitoring technique is strongly dependent on the signal-to-noise ratio. Cultural and ambient noise usually dominate the data, thereby decreasing the effectiveness of surface microseismic techniques in identifying and locating microseismic events. Hence, suppression of noise is a critical step in surface microseismic monitoring.

In surface microseismic data, stacking-based techniques are commonly used to locate
microseismic events within noise (Kiselevitch et al., 1991; Kao & Shan, 2004; Kochnev et al., 2007; Duncan & Eisner, 2010). However, waveform information can rarely be extracted, e.g., it is difficult to determine the polarity of the microseismic waveform at the onset of its arrival at each receiver. Correct estimation of the microseismic source mechanism, which is of prime importance in understanding the focal mechanism of the faults and fractures (Aki & Richards, 2002), depends mainly on the accuracy of the waveform determination. Therefore, it is critical for any noise suppression technique to recover/preserve the correct microseismic waveform while enhancing the signal-to-noise ratio at the same time.

Here, we propose a technique that effectively suppresses noise in microseismic records and also preserves the waveform. With this technique, which is based on transforming the data to the \( \tau - p \) domain, we can separate microseismic events from surface-noise based on distinct characteristics that are not visible in the time-offset \( (t - x) \) domain (Bungum & Capon, 1974; Neele & Snieder, 1991).

### 5.3 Theory

The dominance of noise in surface microseismic data masks many microseismic events recorded. Therefore, transforming the data to a domain such as \( \tau - p \), in which the characteristics of surface noise and microseismic events can be separated, provides the opportunity to identify microseismic events within the record.

The \( \tau - p \) transform (also called slant-stack) maps a linear event in the \( t - x \) domain to a point in the \( \tau - p \) domain such that the coordinates of that point correspond to the slope and time intercept of the linear event. In addition, an event with hyperbolic moveout in \( t - x \) domain is mapped to a parabolic-shaped event in the \( \tau - p \) domain. In fact, this transform decomposes a waveform to a series of lines that can be mapped to a series of points in the \( \tau - p \) domain. The \( \tau - p \) transform is given by

\[
U(p, \tau) = \int U(x, t) \, dx = \int U(x, \tau + px) \, dx, \tag{5.1}
\]

(Claerbout, 1985), where \( U(t, x) \) represents the data in the \( t - x \) domain as a function
of recording time ($t$) and source-receiver offset ($x$); $\bar{U}(p, \tau)$ represents the data in the $\tau - p$ domain as a function of intercept ($\tau$) of an event with the time axis and the slope or horizontal slowness ($p$) of the event in the data.

Our proposed noise suppression method is based on transforming the data to the $\tau - p$ domain and isolating the upcoming microseismic events from the surface-noise. This is followed by an inverse $\tau - p$ transform to obtain the isolated microseismic event in the $t - x$ domain. Further details on the implementation of the method are given below.

5.4 Data description

The data used here were acquired by ConocoPhillips in the Greater Dallas area, over a Barnett shale reservoir undergoing a hydraulic fracturing process along two horizontal wells (Forghani et al., 2011). Figure 5.1 illustrates the location of the horizontal wells and the receiver array used in this acquisition. Receivers in the outer (blue) and central (red) arrays have separate recording systems. In this study, we employ only the data recorded in the central part of the array (Figure 5.2). Table 5.1 shows the acquisition parameters for the central array.

The passive data available to us were recorded before the onset of the hydraulic frac-
Figure 5.2: Plan view of the central receiver array. The black star is the surface location of a synthetic microseismic event.

---

Table 5.1: Data acquisition parameters of the surface passive seismic survey

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Rate</td>
<td>2 ms</td>
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<tr>
<td>Receiver Frequency Range</td>
<td>6-200 Hz</td>
</tr>
<tr>
<td>Number of Receivers</td>
<td>1100</td>
</tr>
<tr>
<td>Receiver Interval</td>
<td>100 ft</td>
</tr>
<tr>
<td>Receiver Component</td>
<td>Vertical</td>
</tr>
</tbody>
</table>
turing process; therefore no microseismic events are present in these data. However, using regional information about the approximate depth of induced microseismic events by hydraulic fracturing and the average subsurface seismic velocity we created synthetic microseismic events and superimposed them on the recorded passive data to make pseudo-synthetic data. Combining synthetic microseismic events with passive noise recorded in the field is sufficient for testing our technique (Chambers et al., 2010). Most microseismic sources have a mechanism similar to that of a double-couple (Rutledge & Phillips, 2003), while some (such as perforation shots) are more isotropic; so we evaluate noise suppression as applied to microseismic events with each source mechanism.

5.5 Microseismic event with isotropic source mechanism

In the first example, we construct a synthetic microseismic event with an isotropic source, located at the reservoir depth in the center of the array (black star in Figure 5.2). For an isotropic source, the recorded waveform of the microseismic event has the same polarity at all the receivers across the array. Figure 5.3 illustrates the portion of the passive data that contains this microseismic event. Note that the signal-to-noise ratio is estimated by dividing the root mean square (RMS) amplitude of the signal by that of the noise.

In order to transform the data from $t - x$ to $\tau - p$ domain, we first sort the receivers according to offset from the epicenter of the microseismic event (based on the assumption that we know the epicenter of the event). We then apply an approximate moveout shift to all traces, proportional to their source-receiver offset, to horizontally align the event (Figure 5.4). The advantage of removing the event moveout is to obtain a better focusing and isolation of the event in the $\tau - p$ domain.

We then apply the $\tau - p$ transform to the gather in Figure 5.4 to obtain the $\tau - p$ domain image as shown in Figure 5.5. The high amplitude region in this domain corresponds to the range of slownesses and time intercepts of the moveout-corrected microseismic data. Note that the event in the $\tau - p$ domain is focused about zero slowness because of the moveout correction.
Figure 5.3: Surface passive data with an added isotropic microseismic event at about 2.7 seconds. Signal-to-noise (S/N) ratio is about 2.

Figure 5.4: Same data as in Figure 5.3 after sorting and moveout correction. Receivers are sorted according to their distance from the epicenter of the microseismic source.
We then isolate this high amplitude area (microseismic event) from the passive noise in the $\tau - p$ domain by amplitude thresholding and apply the inverse $\tau - p$ transform to return the microseismic event back to $t - x$ domain (Figure 5.6).

Comparing Figures 5.3 and 5.6, we can observe that the signal-to-noise ratio for the microseismic event has increased. In order to confirm that our noise suppression technique has preserved the waveform of the microseismic event, we compare the waveforms at one of the receivers before and after noise suppression. Figure 5.7 illustrates three waveforms recorded at one of the receivers, the waveform of: 1) the synthetic microseismic event, 2) the microseismic event combined with the passive data before noise suppression, and 3) the resulting microseismic event after noise suppression. Comparison of the three waveforms shows that by applying the $\tau - p$ transform, the signal-to-noise ratio of the microseismic event is increased noticeably, and more importantly, the waveform of the microseismic event is preserved.

5.6 Microseismic event with double-couple source mechanism

For a double-couple source, the polarity of the recorded waveform of a microseismic event changes at receivers across the array. Radiation pattern of such a source consists of four lobes with opposite polarities for adjacent lobes. Figure 5.8 illustrates a simplified
Figure 5.6: Noise suppression result for the isotropic microseismic event in Figure 5.3. The resulting signal-to-noise ratio is approximately 20.

Figure 5.7: Comparison of three waveforms: synthetic microseismic event (green), data containing the microseismic event (blue), and result of noise suppression (red), for the isotropic source at one receiver location.
radiation pattern of a synthetic microseismic event with a double-couple source located in the center of array (same point as the isotropic source). The fault plane is considered to be vertical and the direction of the coupled-forces that create such microseismic event is shown with the black arrows.

Figure 5.9 illustrates the time window of the passive data that contains this microseismic event. After sorting these data based on the distance of the receivers from the surface location of the microseismic event and applying the corresponding moveout shift, we obtain the data as shown in Figure 5.10.

In Figure 5.10 one can observe different polarities at different receivers. Identification of a microseismic event in $\tau - p$ domain is possible if the recorded waveforms at the receivers interfere constructively, which happens when the polarity of an event is the same at all the receivers. In the case of double-couple sources the opposing polarities of the microseismic waveforms cancel each other when applying $\tau - p$ transform to the sorted data such that there is no high amplitude area in the $\tau - p$ domain. As a result, separation and suppression of the microseismic event in $\tau - p$ domain is problematic. Therefore, before applying the $\tau - p$ transform, we apply a cross-correlation based technique to make the polarity of the microseismic event uniform at all receivers.
Figure 5.9: Surface passive data with added double-couple microseismic event at about 2.7 seconds. Receivers are sorted according to the receiver lines and S/N is about 2.

Figure 5.10: Same data as in Figure 5.9 after sorting and moveout correction. Receivers are sorted according to their distance from the epicenter of the microseismic source.
In this technique we determine the polarity of the waveform at each trace by selecting a time window encompassing the microseismic event and then cross-correlating each trace with a pilot trace selected from the same window. The cross-correlation estimates the waveform similarity between each trace and the pilot trace at the time of the microseismic arrival. If the polarity of a particular trace is similar to that of the pilot trace, the maximum of the cross-correlation has a positive value; otherwise, it has negative value. If the cross-correlation maximum for a trace is negative, we reverse the polarity of that trace; if the cross-correlation maximum is positive, we leave the polarity of the trace unchanged. Figure 5.11 shows the data of Figure 5.10 after making the polarities uniform using our cross-correlation based technique.

Next, we apply the $\tau - p$ transform to the data in Figure 5.11 and obtain the image in Figure 5.12. After isolating the microseismic event in $\tau - p$ domain with a method similar to that used for the isotropic source example, we apply the inverse $\tau - p$ transform to return the microseismic data back to the time-offset domain. Note that after transferring the data back to the time-offset domain, we restore the polarities to their original values, undo the applied shift and moveout and then sort the data back to the original receiver line (Figure 5.13).

Comparing Figures 5.9 and 5.13, we observe improvement of signal-to-noise ratio for
Figure 5.12: $\tau - p$ transform of the data in Figure 5.11 (double-couple source).

Figure 5.13: double-couple microseismic event after applying noise suppression in $\tau - p$ domain and inverse $\tau - p$ transform of Figure 5.12. Signal-to-noise ratio is about 15.
this microseismic event. In order to investigate whether the waveform of the microseismic event is preserved by our noise suppression, we compare the waveforms at one receiver before and after the noise suppression (Figure 5.14). Clearly, not only has the signal-to-noise ratio of the microseismic event been greatly improved, but the microseismic waveform has been preserved.

Although our technique is successful at suppressing the noise and preserving the waveforms, the polarity of some of the traces with low signal-to-noise ratio is reversed incorrectly. For example by comparing Figures 5.9 and 5.13, one can observe that polarities of traces around trace number 600 are reversed. This is due to the inaccuracy of the cross-correlation algorithm in polarity recognition in the case of low signal-to-noise ratio.

Next, we investigate the effectiveness of this noise suppression method for different signal-to-noise ratios. We study three events with the same source characteristics (location and mechanism) but different signal-to-noise ratios. Figures 5.15(a), 5.15(d) and 5.15(g) show the three time windows of the passive data (similar to the data in Figure 5.9) with the signal-to-noise ratios of 1, 1.5, and 3, respectively. Using our noise suppression algorithm, we obtain Figures 5.15(b), 5.15(e) and 5.15(h) with the average signal-to-noise ratios of 1.5, 10, and 25, respectively. The corresponding waveforms of one of the traces at these three
time windows are shown in Figures 5.15(c), 5.15(f) and 5.15(i). We can observe that for a signal-to-noise ratio as low as 1 (such as in Figures 5.15(a) and 5.15(c)), our noise suppression technique is not effective in the recovery of the microseismic event.

5.7 Discussion and Conclusion

We have introduced a technique that is effective at noise suppression in surface microseismic records. This technique, which is based on the $\tau - p$ transform, allows us to identify and separate microseismic events from the noisy data even with the signal-to-noise ratio as low as unity. We applied our technique to two microseismic events with different source mechanisms, an isotropic and a double-couple source. For the isotropic source the polarity at all the receivers across the array is the same, and we directly apply the $\tau - p$ transform to the data and achieve a significantly improved signal-to-noise ratio and a preserved waveform. For the case of a double-couple source, since the polarity of the microseismic event changes with receiver location, we use a cross-correlation based technique to make the polarity across the receivers uniform prior to applying the $\tau - p$ transform. Even with this additional processing step, our method suppresses the noise significantly and preserves the original waveform. However, our noise suppression technique becomes less effective as the signal-to-noise ratio decreases; for signal-to-noise ratios approaching 1, proper reconstruction of the signal becomes challenging.

In the above examples of semi-synthetic passive data, we consider a uniform waveform that is the same for all the azimuths. Therefore, we include the receivers across the whole array in our $\tau - p$ transform, that gives rise to the number of receivers in the summation of the $\tau - p$ transform. However, in real microseismic data the recorded microseismic waveform changes with azimuth. Therefore, instead of the whole receiver array, receivers in a specific azimuth can be used in the $\tau - p$ transform. For this case, it would be useful to investigate the number of receivers necessary as well as the receiver spacing required for effective noise suppression. The above topics are all under investigation.
Figure 5.15: a), d), and g): The surface passive data with added double-couple microseismic event at about 2.7 seconds with the signal-to-noise ratios of 1, 1.5, and 3, respectively. b), e), and h) are the passive data after applying noise suppression with the $\tau - p$ with the signal-to-noise ratios of 1.5, 10, and 25, respectively. c), f), and i): Comparison of three waveforms at one of the receivers in the array: synthetic microseismic event (green), combined microseismic event and passive data before noise suppression (blue), and combined microseismic event and passive data after noise suppression (red).
Acknowledgment

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Chapter 6

AN EFFECTIVE NOISE SUPPRESSION TECHNIQUE FOR SURFACE MICROSEISMIC DATA

6.1 Abstract

The presence of strong surface-wave noise in surface microseismic data may decrease the utility of these data. We implement a technique, based on the distinct characteristics that microseismic signal and noise show in the $\tau - p$ domain, to suppress surface-wave noise in microseismic data. Because the majority of microseismic source mechanisms are anisotropic, pre-processing is necessary to correct for the non-uniform radiation pattern prior to transforming the data to the $\tau - p$ domain. We employ a scanning approach, similar to semblance analysis, to test all possible double-couple orientations in order to determine an estimated orientation that best accounts for the polarity pattern of any microseismic events. We then correct the polarity of the data traces according to this pattern, prior to conducting signal-noise separation in the $\tau - p$ domain. We apply our noise suppression technique to two surface passive seismic datasets from different acquisition surveys. The first dataset includes a synthetic microseismic event added to field passive noise recorded by an areal receiver array distributed over a Barnett shale reservoir undergoing hydraulic fracturing. The second dataset is a real/field microseismic data recorded by receivers arranged in a star-shaped array, over a Bakken shale reservoir during a hydraulic fracturing process. Our technique significantly improves the signal-to-noise ratios of the microseismic events and preserves the waveforms at the individual traces. We illustrate that the enhancement in signal-to-noise ratio also results in improved imaging of the microseismic hypocenter.
6.2 Introduction

Low-permeability reservoir rocks such as shales and tight-gas sandstones are commonly stimulated using hydraulic fracturing to increase their permeability and enhance production. In order to maximize productivity, it is critical to distinguish zones that have been affected by hydraulic fracturing from zones that have not. A novel way of unraveling these zones is to monitor the seismicity resulting from fracturing and stress changes. The magnitude of these hydraulic-fracturing-induced seismic events is mostly less than 1, and they are usually referred to as microseismic events. Monitoring of such microseismicity is usually done using sensors placed in a monitor wellbore that is close to the rocks being fractured. Downhole monitoring, however, provides a limited recording aperture that may impose inaccuracy in microseismic hypocenter imaging or source mechanism estimation (Thornton & Eisner, 2011).

Surface monitoring is becoming more common in analyzing the hydraulic fracturing process (Duncan, 2005; Kochnev et al., 2007). Because of the potentially larger receiver aperture and higher number of receivers, surface microseismic data may be more informative than downhole data (Eisner et al., 2010; Chambers et al., 2010; Duncan & Eisner, 2010). However, surface noise in the form of cultural and ambient noise decreases the signal-to-noise ratio in the surface microseismic data, thereby making the identification and location of microseismic events challenging. In the presence of noise, processing steps (such as imaging) introduce artifacts and inversion (such as waveform inversion) introduces errors in the estimated velocity model and the source parameters. Therefore, noise suppression is a critical step in the processing of surface microseismic data.

Conventional noise suppression techniques such as stacking-based techniques rely on enforcing the amplitude of the signal by stacking the waveforms at the receivers (Kiselevitch et al., 1991; Kao & Shan, 2004; Kochnev et al., 2007; Duncan & Eisner, 2010). However, waveforms at the individual receivers, which are necessary for estimating microseismic source location and source mechanism (Aki & Richards, 2002) cannot be extracted after processing with such methods.
Forghani et al. (2012) proposed a noise suppression technique for the surface microseismic data based on transforming the data to the $\tau - p$ domain. Their algorithm not only improves the signal-to-noise ratio of visible events, but also preserves the waveform at the individual receivers. In the time-offset ($t - x$) domain, the characteristics of microseismic events might not be different from that of surface noise. In a different domain, such as $\tau - p$, however, their character might be different which would help us separate them.

While Forghani et al. (2012) considered two types of source mechanisms generating uniform and non-uniform polarities across the receiver array, their implemented source mechanism was very simple and did not include the realistic mechanism for which the radiation pattern is estimated based on the orientation of the fracture-plane. In this paper, although we follow on the footsteps of some of their processing, we introduce multiple enhancements to their algorithm resulting in improved noise suppression and better handling of field data.

We implement a more realistic microseismic source mechanism, where the polarities and the amplitude of the recorded waveforms vary with the take-off direction. Moreover, while Forghani et al. (2012) used cross-correlation for the polarity recognition, we suggest a more stable semblance-based approach that performs better, especially in the case of low signal-to-noise ratios and realistic polarity variations. Other enhancements to the algorithm are described later in the context of their application to data examples.

First, we introduce the theory for the techniques that are used in this study and provide a flowchart for the processing steps. We then present the results of applying the noise suppression algorithm to two datasets; a semi-synthetic dataset with the areal layout and a real/field microseismic dataset with a star-shaped array. After testing the noise suppression algorithm on the field records, we demonstrate the benefits of noise suppression on reverse-time imaging of the microseismic data.

6.3 Methodology and processing steps for noise suppression

The $\tau - p$ transform (Equation A.1), or slant-stack, is obtained by summation over offset of waveforms for a range of slopes or horizontal slownesses ($p$) and time intercepts ($\tau$). This
transform has long been used for signal/noise separation purposes in active data (Durani & Bisset, 1984; Dunne & Beresford, 1995) and is described in more detail by Claerbout (1985) and Stolt & Weglein (2012). The summation maps an event with a linear moveout in the \( t - x \) domain to a point in the \( \tau - p \) domain such that the coordinates of the point in the \( \tau - p \) domain correspond to the time intercept and the slope of the linear event in the \( t - x \) domain. A hyperbolic event in the \( t - x \) domain is mapped to an elliptical event in the \( \tau - p \) domain (Claerbout, 1985).

Forghani et al. (2012) exploit the separation that occurs in the \( \tau - p \) domain for the signal and the noise in microseismic data and demonstrate its effectiveness on the noise suppression for simple source mechanisms. In order to utilize the \( \tau - p \) transform for microseismic data containing events with complicated source mechanisms (commonly double-couple mechanism), we must process the data to make sure that the opposing polarities of the events do not interfere destructively in the \( \tau - p \) domain (Forghani et al., 2012).

### 6.3.1 Moveout correction

Two processes are involved in unifying the polarity of any event – detection of the moveout of the event and identification of the polarity change across the receiver array. In the first step, we follow a semblance approach to compute the moveout that is able to flatten the event about its epicenter or remove the nonlinear moveout character of the event from the receiver waveforms. Prior to this step, a separate initial scanning for the epicenter might be necessary for low signal-to-noise ratio (SNR) events. However, since our primary goal is to clean up already visible events, we assume that the apex of the hyperbola of the visible event corresponds to its epicenter. In our semblance analysis, we assume the subsurface to be laterally homogeneous and azimuthally isotropic. In the presence of anisotropy, one might need a higher-dimensional semblance analysis and non-hyperbolic moveout correction. The hyperbolic moveout time \( t_m \) for an isotropic medium is given by

\[
t_m = \sqrt{\frac{t^2}{\frac{z^2}{v^2} + \frac{h^2}{v^2}}} + t_0,
\]

(6.1)
where $z$ is the source depth, $v$ is the moveout velocity and $h$ is the offset (distance between the source epicenter and the receiver); $t_{sr}$ denotes the travel-time from the source to the receiver and $t_0$ is the initiation time of the source. There are three unknowns in equation 6.1 - the source depth ($z$), moveout velocity ($v$), and the source-initiation time ($t_0$). Therefore, to extract the best-fit moveout times, one needs to scan over $z$, $v$, and $t_0$. Note that we are only interested in finding the best-fit moveout time $t$ and are not concerned with the accuracy of the moveout parameters $z$, $v$, and $t_0$ obtained from semblance analysis. In fact, multiple combination of $z$, $v$, and $t_0$ can yield similar moveout times.

For an event that is visible on the seismograms, we can use the recorded time at zero-offset receiver $t_{(m,h=0)}$ to replace $t_0$ in equation 6.1 by substituting

$$t_0 = t_{(m,h=0)} - \frac{z}{v}, \quad (6.2)$$

thereby reducing the number of scanning parameters in semblance from three to two. The semblance is then carried out by scanning over a range of user-defined values for the source depth and moveout velocity using the expression

$$t_m = \sqrt{\frac{t_{sr}}{z^2 + h^2}} + t_{(m,h=0)} - \frac{z}{v}. \quad (6.3)$$

The combination of these two parameters ($z$ and $v$) with the highest value of semblance, yields the best-fit traveltime moveout.

The measure of semblance used here is given by

$$S(z, v) = \sum_{t=t_m-\Delta t/2}^{t_m+\Delta t/2} \sum_{h=h_1}^{h_N} d^2(t, h), \quad (6.4)$$

where $d(t, h)$ represents the recorded data, $t_m$ is the traveltime moveout (for any combination of $z$ and $v$), $\Delta t$ is the time window encompassing the event, $h$ is the receiver offset and $h_1$ and $h_N$ denote the offsets for the first and last receivers, respectively. Note that the semblance measure in equation 6.4 is different from the conventional semblance formula. We suggest
this modified semblance because it is insensitive to the waveform polarity and only depends on the ‘energy’ in the data along the moveout time $t_m$. This eases the issue of polarity-variation of the event across the receiver array. The performance of the above measure of semblance, however, would worsen with decreasing signal-to-noise ratio.

### 6.3.2 Accounting for polarity change

One possible approach to determine the polarity of the waveform at each trace is to cross-correlate each trace with a pilot trace that has a known polarity (Forghani et al., 2012). The cross-correlation estimates the waveform similarity between each trace and the pilot trace at the time of the microseismic arrival. Based on the sign of the cross-correlation coefficient, the sign of the polarity of each trace can be recognized. However, in the case of low signal-to-noise ratio and/or improper choice of pilot trace, the cross-correlation technique becomes less accurate in determining the polarity (Forghani et al., 2012). Here, we propose a second scanning routine to determine the radiation pattern of the double-couple source and use that for determining the polarity.

For a double-couple source, the polarity of the recorded waveform of a microseismic event changes at receivers across the array based on the radiation pattern. In the datasets used in this study, the only recorded component is the vertical component, therefore, we use only the P-wave radiation pattern. P-wave radiation pattern of a double-couple source can be mathematically described by three angles (Equation B.3): strike $\phi$, dip $\theta$ and slip $\psi$, which denote azimuth and dip of the fracture-plane, and the slip direction on the plane, respectively.

In order to compute the best-fit radiation pattern, we first select a time window encompassing the microseismic event at all the receivers. This window is given by the best-fit moveout parameters obtained from scanning for $z$ and $v$ above. Next, we loop over every combination of strike, dip and slip angles and compute the radiation pattern $R_p$ at every receiver location using Equation B.3. Thereafter, the semblance $S(\phi, \theta, \psi)$ is computed using
where \( sgn \) is the sign function and \( t_m \) is the best-fit traveltime moveout computed above. The highest semblance corresponds to the best-fit values of \( \phi \), \( \theta \), and \( \psi \). Note that these semblance-derived values might not correspond to the true \( \phi \), \( \theta \), and \( \psi \). The radiation pattern corresponding to these best-fit angles is then used to unify the polarity of the receiver waveforms. This is accomplished by reversing the polarity of only those traces whose predicted polarity is negative while leaving those with positive polarity unchanged.

### 6.3.3 Noise suppression

The input to the \( \tau - p \) transform is the data that has undergone moveout correction about the epicenter using the best-fit \( t_m \) as well as polarity unification as described above. Ideally, the event would plot to a point on the \( p = 0 \) axis in the \( \tau - p \) domain after the above processing steps. If the source signature is complicated, the event would still focus on the \( p = 0 \) axis but would be dispersed along the \( \tau \) axis depending on the duration of the source signature. Noise on the other hand will appear random in the \( t - x \) space (for a noise source coinciding with the epicenter, however, the noise will not be random; this scenario is discussed below). In addition, the noise will also get spread in the \( \tau - p \) domain as a result of the transformation. We use a smoothing operator to suppress this random noise in the \( \tau - p \) domain. Alternatively, one could use a threshold or surgical muting to preserve the event focus and suppress the noise. Isolation of the microseismic event in the \( \tau - p \) domain is followed by an inverse \( \tau - p \) transform (Equation A.13) to obtain the noise-suppressed microseismic event in the \( t - x \) domain. Thereafter, the moveout correction originally applied is removed and the polarities are restored to their original form. The above processing steps are summarized in a flowchart in Figure 6.1. In the next sections, some of the above routines are described in more detail in the context of their application to data.
6.4 Semi-synthetic microseismic data recorded by an Areal Receiver Array

These passive data were acquired by ConocoPhillips over a Barnett shale reservoir, in the Greater Dallas area, undergoing a hydraulic fracturing process along two horizontal wells (Forghani et al., 2011, 2012). Figure 6.2(a) illustrates the receiver layout used in this acquisition. The acquisition parameters for this array are shown in Table 6.1 (Forghani et al., 2012, 2011).

The data available to us are acquired before the start of the hydraulic fracturing process, hence they do not include any induced microseismic events (Forghani et al., 2012). In order to test our noise suppression technique, we generate a synthetic microseismic event using a typical reservoir depth of 3 km and the average subsurface P-wave velocity of about 4000 m/s and superimpose this event with the passive data recorded at the field to form a semi-synthetic dataset [as was done by Chambers et al. (2010) and Forghani et al. (2012)].

We use a double-couple source mechanism for the synthetic microseismic event by defining the fracture-plane orientation through Euler angles. Figure 6.2(b) illustrates the radia-
Table 6.1: Data acquisition parameters of the surface passive seismic survey with an areal receiver array.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Rate</td>
<td>2 ms</td>
</tr>
<tr>
<td>Receiver Frequency Range</td>
<td>6-200 Hz</td>
</tr>
<tr>
<td>Number of Receivers</td>
<td>1197</td>
</tr>
<tr>
<td>Receiver Interval</td>
<td>30 m</td>
</tr>
<tr>
<td>Receiver Component</td>
<td>Vertical</td>
</tr>
</tbody>
</table>

The polarization pattern of this microseismic event for a vertical fracture-plane located directly beneath the receiver patch with fracture-normal along the $x$-axis and slip along the $y$-axis such that strike, dip and slip angles are given by $\phi = 90^\circ$, $\theta = 90^\circ$ and $\psi = 0^\circ$, respectively. Note that for the receivers located in the nodal regions the amplitude of the recorded data is close to zero.

Figure 6.3(a) illustrates the time window of the passive data that contains the synthetic microseismic event. The in-line and cross-line directions are defined to be along the $y$- and $x$-axes, respectively. Data from the receiver in-lines are displayed next to each other in Figure 6.3(a) with increasing $y$-coordinate within each in-line. Every hyperbola in this figure corresponds to the microseismic event recorded by a receiver line such that the first hyperbola (traces 1-36) represents the microseismic event at receiver in-line 1 [the left-most receiver line in Figure 6.2(b)]. Note the change in polarity within each receiver in-line and the low-amplitude at the nodal regions (center of the hyperbola). Figure 6.3(b) shows the data after moveout correction computed using the semblance-derived best-fit parameters and Figure 6.3(c) shows the data after unifying the polarities.

Next, we apply the $\tau - p$ transform to the data in Figure 6.3(c) and obtain the image in Figure 6.3(d). The high amplitude region in this domain corresponds to the range of slownesses and time intercepts of the moveout-corrected microseismic event. Note that the event in the $\tau - p$ domain is well focused about zero slowness because of the moveout.
Figure 6.2: (a) Map view of the areal receiver array; gray dots represent the receivers. The two black lines denote the horizontal wells, the black filled square shows the well head, and the black empty squares represent the well bottom (Forghani et al., 2012, 2011). (b) P-wave radiation pattern due to a double-couple source located in the center of the array at the reservoir depth; red and blue represent positive and negative polarities, respectively.
Figure 6.3: (a) Surface passive data with added microseismic event from a double-couple source, recorded at about 2.75 seconds. Data are sorted according to the receiver in-lines. The signal-to-noise ratio which is estimated by dividing the root mean square (RMS) amplitude of the signal by that of the noise is about 2. (b) Same data as in Figure 6.3(a) after moveout correction. (c) The same data as in Figure 6.3(b) after unifying the polarity of the double-couple event using our semblance-based technique. (d) $\tau - p$ transform of the data in Figure 6.3(c).
correction. We enhance this high amplitude area (microseismic event) from the passive noise in the $\tau - p$ domain using a smoothing filter. The smoothing is done by convolving the $\tau - p$ data with a 2D normalized boxcar function. The window size is selected such that the size of the boxcar function is less than the event size in the $\tau - p$ domain. Alternatively, one could also simply isolate the event in $\tau - p$ domain by windowing or use a median filter. After isolating the microseismic event by smoothing we apply the inverse $\tau - p$ transform to return the event back to $t - x$ domain. We then restore the trace polarities to their original values and undo the applied moveout shift to return the data back to the original format [Figure 6.4(a)].

Comparing Figures 6.3(a) and 6.4(a), we observe substantial improvement in the signal-to-noise ratio for this microseismic event. In order to investigate whether the waveform of the microseismic event is preserved by our algorithm, we compare the waveforms at a receiver (Figure 6.4(b)) located at an off-nodal region before and after noise suppression. The waveforms in Figure 6.4(b) demonstrate that our noise suppression technique has not only enhanced the signal-to-noise ratio of the microseismic event, but also the microseismic
Table 6.2: Data acquisition parameters of the star-shaped acquisition in Figure 6.6(a).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Rate</td>
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</tr>
<tr>
<td>Receiver Frequency Range</td>
<td>5-200 Hz</td>
</tr>
<tr>
<td>Number of Receivers</td>
<td>1242</td>
</tr>
<tr>
<td>Receiver Interval</td>
<td>25 m</td>
</tr>
<tr>
<td>Receiver Component</td>
<td>Vertical</td>
</tr>
</tbody>
</table>

waveform has been preserved.

**Effect of signal-to-noise ratio** In order to investigate the effectiveness of our algorithm for different levels of noise, we conduct tests on data with different signal-to-noise ratios. Three events with the same source characteristics [location and mechanism are similar to the data in Figure 6.3(a)] but different signal-to-noise ratios are shown in Figures 6.5(a), 6.5(d) and 6.5(g) with the signal-to-noise ratios of 1.5, 0.8, and 0.6, respectively. Figures 6.5(b) and 6.5(e) illustrate the noise suppressed data with the average signal-to-noise ratios of 30 and 4, respectively. Note that even for as low a signal-to-noise ratio as 0.8 (such as in Figure 6.5(d)), our noise suppression technique is effective in the recovery of the microseismic event. However, for lower signal-to-noise ratios such as 0.6 in Figure 6.5(g) the noise suppression is not effective. The corresponding waveforms of one of the traces at these three time windows are shown in Figures 6.5(c), 6.5(f) and 6.5(i).

6.5 Real/field surface microseismic data recorded by a star-shaped array

The second dataset used here was acquired by Whiting Oil and Gas over a Bakken Formation reservoir during a hydraulic fracturing process in North Dakota. The receivers in this survey are distributed in a star-shaped array containing 10 receiver lines, also called as receiver arms [Figure 6.6(a)]. Table 6.2 shows the acquisition parameters for this array.

Figure 6.7(a) shows a portion of the data containing a microseismic event recorded by
Figure 6.5: a), d), and g): Surface passive data with added microseismic event from a double-couple source, recorded at about 2.75 seconds with the S/N of 1.5, 0.8 and 0.6, respectively. b), e), and h) are the passive data after applying noise suppression with the increase in S/N up to 30 and 4, respectively, for the data in a) and d). c), f), and i): Comparison of three waveforms at receiver number 115: synthetic microseismic event (dotted gray), combined microseismic event and passive data before noise suppression (gray), and combined microseismic event and passive data after noise suppression (black).
Figure 6.6: (a) Star-shaped acquisition pattern containing 10 arms (receiver lines) used for surface microseismic monitoring over the Bakken Formation reservoir; black dots represent the receivers. (b) Predicted polarity at receivers using the semblance-based technique corresponding to a fracture-plane with strike, dip and slip angles of $\phi = 30^\circ$, $\theta = 70^\circ$, and $\psi = 100^\circ$, respectively.

The data at many receivers is contaminated with electric-hum noise. The frequency content of this noise is 60 Hz which is different from the frequency range of most microseismic events at the surface (10-30 Hz). Therefore, to remove the electric-hum and other noises outside the microseismic bandwidth, we apply a band-pass filter with the frequency range of 10-55 Hz to obtain the filtered data shown in Figure 6.7(b).

We then apply the $\tau - p$ domain noise suppression technique described above to the filtered data in Figure 6.7(b). In order to prepare the data for the forward $\tau - p$ transform, we follow the same procedure as described above, such as applying the moveout shift and unifying the polarities. Using the semblance-based technique and assuming that this microseismic event is generated by a double-couple source, we predict the polarities at the receivers (Figure 6.6(b)). The best-fit orientation of the fracture-plane and the slip vector estimated by semblance analysis are given by $\phi = 30^\circ$, $\theta = 70^\circ$, and $\psi = 100^\circ$.

Figure 6.7(c) shows the input data for the $\tau - p$ transform. Note that because static
corrections are not applied to the data, the microseismic event is not perfectly aligned. The resulting $\tau - p$ transformed data is shown in Figure 6.7(d). The high amplitude region in Figure 6.7(d) corresponds to the moveout- and polarity-corrected microseismic event. After isolating this microseismic event from the passive noise in the $\tau - p$ domain, applying the inverse $\tau - p$ transform, and restoring the data back to their original moveout and polarity, we obtain the data shown in Figure 6.8(a). Comparing Figures 6.7(b) and 6.8(a), we observe a noticeable improvement in the signal-to-noise ratio.

However, here we have disregarded the azimuthal information of the 3D data by using a 2D forward $\tau - p$ transform. Therefore, the relative amplitude of the microseismic event across the receiver array will not be preserved. Moreover, the smoothing operation in the $\tau - p$ domain will lead to leakage of energy into other traces. As a result the waveforms of the original microseismic event (Figure 6.7(b)) deviate from the waveforms of the recovered event (Figure 6.8(a)). These discrepancies are more visible for receiver numbers close to 700 and 1000. Lack of amplitude preservation is also very clear on trace 380 where an abrupt change from positive to negative occurs.

The above issue can possibly be addressed by using a 3D $\tau - p$ transform (Chapman, 1981) or performing sector-wise noise suppression using the 2D $\tau - p$ technique described above. Here, we adopt the latter approach to investigate the results of applying the noise suppression technique to data from different azimuths. We divide the receiver array into a few azimuthal sectors with each sector containing sufficient number of traces to obtain a proper focusing in the $\tau - p$ domain. Sectors are defined with the source epicenter as the origin. The number of sectors is chosen so as to strike a balance between having sufficient number of receivers and keeping the sector size small. After testing different sector sizes, we use seven azimuthal sectors (each spanning approximately 50°) with every sector comprising at least 150 traces. Thereafter, we apply the above noise suppression technique to each of the seven sectors independently. The result of this sector-wise noise suppression is shown in Figure 6.8(b).

Comparing Figures 6.7(b), 6.8(a), and 6.8(b), we observe that sector-wise noise suppression preserves the azimuthal waveform variations better than noise suppression applied
Figure 6.7: (a) A real microseismic event recorded at about 3.2 seconds. Receivers are sorted according to the receiver arms. (b) Filtered data in Figure 6.7(a) with a band-pass filter of 10-55 Hz. (c) The same data as in Figure 6.7(b) after moveout correction and equalizing the polarity of the microseismic event using our semblance-based technique. (d) $\tau - p$ transform of the data in Figure 6.7(c).
Figure 6.8: (a) Data obtained by noise suppression applied to receivers in whole array. (b) Result of sector-wise application of the noise suppression algorithm.

to all azimuths at once. In sector-wise noise suppression, however, having a small number of receivers (approximately 150) in each sector might limit the effectiveness of the algorithm at suppressing the noise. On the other hand, including all the receivers (1242) can result in a better focusing in the $\tau - \rho$ domain and consequently more effective noise suppression.

6.5.1 Imaging

Microseismic hypocenter locations are commonly determined by imaging the data. The quality of the image, and therefore the success at locating hypocenters, strongly depends on the signal-to-noise ratio of the data. Here, we demonstrate the advantage of performing imaging using noise-suppressed data (Figure 6.8(a)) relative to raw data (Figure 6.7(b)).
Imaging of microseismic data is usually performed either using a diffraction-stacking approach (Gajewski et al., 2007) or a reverse-time approach (McMechan, 1982; McMechan et al., 1983). Both imaging techniques require a velocity model for ray-tracing and wavefield reconstruction, respectively. Here, we use the reverse-time approach under which the receiver wavefield is reconstructed in space and time by back-propagating the recorded data. Back-propagation corresponds to reversing the recorded data in time, injecting it into the velocity model, and computing the wavefield. We use a two-dimensional finite-difference algorithm for computing the wavefield. If the velocity model is accurate, any microseismic event will focus at the correct hypocenter at the initiation time of the seismicity. Thus, source location and initiation can be deciphered by locating spatial and temporal focusing in the reconstructed wavefield.

In the presence of noise, however, locating the focus becomes challenging. For example, the focus at $x = 0.58$ km and $z = 2.7$ km in Figure 6.9(a) corresponding to the microseismic event in the data before noise suppression (Figure 6.7(b)), is hardly noticeable. Even though the microseismic event in Figure 6.7(b) is quite strong, the presence of noise has substantially limited the efficacy of source location using imaging. Therefore, the presence of noise in the data can lead to many false positives in microseismic-data imaging. On the other hand, the image in Figure 6.9(b) obtained from the data after suppressing the noise (Figure 6.8(a)) is clearly superior to the image in Figure 6.9(a) in identifying the focus. Such substantial reduction in noise should also help in imaging much weaker microseismicity.

6.6 Discussion and Conclusions

We have introduced a technique, based on the $\tau - p$ transform, that allowed us to effectively identify and separate microseismic events from surface wave noise while preserving event waveforms. This approach substantially improved the signal-to-noise ratio for synthetic events added to real surface passive data with starting signal-to-noise ratios as low as 0.8. It also substantially increased signal-to-noise ratio for the field data that include a real microseismic event, and resulted in improved imaging of the hypocenter location via
Figure 6.9: Two-dimensional image of the hypocenter corresponding to the microseismic event in (a) the data before noise suppression (Figure 6.7(b)) and (b) the data after noise suppression (Figure 6.8(a)). The velocity function $V_z$ used for imaging is given by $V_z = 1800 + 0.5z$ m/s, where $z$ is the depth. The velocity model is laterally homogeneous and azimuthally isotropic. Data from a 30° azimuthal sector and its vertically-opposite sector (centered about the event epicenter) containing most of the receivers in arms 1, 10, and 6 (Figure 6.6(a)) are used for generating the above images.
reverse-time migration. The methodology introduced here is not an automated algorithm to identify/detect all microseismic events. The primary purpose of this work is to clean up the events that are already visible or have been detected.

Analysis of this second data set, which was acquired by a star-shaped array, indicated a trade off between the accurate reconstruction of waveforms and the improvement of the signal-to-noise ratio. A radial sector-wise noise suppression preserved the azimuthal waveform variations better than the noise suppression applied to all azimuths at once, however applying the noise suppression to all the azimuths together resulted in a greater improvement in the signal-to-noise ratio. This analysis also indicated that including more arms in a star-shaped array would result in both greater signal-to-noise ratio improvement and better waveform preservation, for example arms spaced at 30° rather than 50°.

Note that various combinations of velocity and depth can yield similar moveout. When we perform semblance scanning over depth and moveout velocity, the moveout parameters might be very different from the actual values; but as long as they flatten the event, they serve their purpose. However, we do not use these moveout parameters for any other purpose. To extract the true source location, one has to perform imaging on the denoised data. As long as the velocity is accurate, imaging can provide the correct hypocenter.

Our approach includes estimation of a double-couple orientation, which is of course directly tied to the fracture orientation. Although fracture orientation is highly valuable information in microseismic monitoring, we caution against using our estimated double-couple orientation as a proxy for fault orientation for several reasons. Our double-couple orientation estimate is intended only to result in optimal unification of event waveform polarities and it is based on an approximate (and likely incorrect) velocity model that neglects important aspects such as anisotropy. Furthermore, our approach makes no effort to resolve the non-uniqueness that exists in the determination of fault orientation from observed waveform polarities. As such, our double-couple orientation estimate may be viewed as very rough auxiliary information only if these limitations kept in mind.

Although non double-couple source mechanisms are reported in some microseismic data (Sileny et al., 2009), most microseismic sources induced by hydraulic fracturing have a mech-
anism similar to that of a double-couple source (Pena et al., 2010). Here, we focused on applying our noise suppression technique only to the microseismic source mechanism of the double-couple type. If other source mechanisms are of interest, one could add another level of scanning over the type of the source mechanism.

When 3D data is transformed to 2D by sorting according to increasing offset from the epicenter, the microseismic event remains coherent while rest of the arrivals get randomized. However, if a noise source is present at the epicenter, arrivals from it would remain coherent and cannot be suppressed using a smoothing operator. For such noise, one has to surgically mute the corresponding region in the $\tau - p$ domain. The above arguments would also mean that 3D $\tau - p$ would not be as effective at suppressing noise using our algorithm because surface noise in 3D would not be as randomized as in the 2D; this hypothesis, however, is yet to be tested.

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Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

Surface microseismic monitoring is becoming more common in analyzing the hydraulic fracturing process, however, the effectiveness of this technique is strongly dependent on the signal-to-noise ratio. Cultural and industrial noise originating from hydraulic fracturing operations usually dominate the data, thereby decreasing the effectiveness of using these data in identifying and locating microseismic events. Hence, noise suppression is a critical step in surface microseismic monitoring. In this thesis, I developed methodologies to suppress noise and improve event identification; I also analyzed noise to extract its properties that can subsequently be used in deciphering near-surface properties.

Event identification on passive seismic data using only a few receivers can be challenging especially when the record lengths span over long durations of time. In Chapter 2, I introduced an automatic event identification algorithm that is designed specifically for event identification on passive data acquired with a small number of receivers. I demonstrated that the conventional \textit{STA/LTA} (Short-term Average/Long-term Average) algorithm is not sufficiently effective in event detection in the common case of low signal-to-noise ratio. With a cross-correlation based method as an extension of the \textit{STA/LTA} algorithm, even low signal-to-noise events (that were not detectable with conventional \textit{STA/LTA}) were revealed. Moreover, because this algorithm looks for local similarities in the \textit{STA/LTA} ratios amongst different receivers, it has the advantage of identifying events common to all receivers. Examples of applying the cross-correlation based \textit{STA/LTA} technique to synthetic data and a field surface passive dataset recorded at a geothermal site, showed the effectiveness of this technique in automatic event identification.
Interferometry is a powerful tool to extract waves (including body-wave and surface-waves) that are propagated from any receiver in the array (called a virtual source) to the other receivers across the array. However, the underestimation of the body-waves and dominant of surface-waves by interferometry in the case of surface source-receiver acquisition has created confusion in the applications of the interferometry and has not been clarified in literature. Through an analysis of applying interferometry to surface source-receiver acquisition in Chapter 3, I demonstrated the reasons behind the under-estimation of body-waves compared to surface-waves. This analysis showed that imperfections in the source distribution at the surface and the lack of subsurface sources, specifically for source locations that had the most contribution in the body-wave reconstruction, were important factors in the under-estimation of the body-waves. This study provided useful insight into the application of interferometry to surface passive seismic data as done in Chapter 4.

Surface-wave characteristics can be used to extract information necessary for suppressing these waves. As I discussed in the introduction, dispersion characteristics of surface-waves is one of the properties of these waves that can reveal helpful information about these waves. When using surface passive records, due to the variability of the uncontrolled sources in time and space, there are no obvious records of surface-wave arrivals that can be used to extract the dispersion properties of these waves. Interferometry specially plays an important role in this case because it can reveal the surface-wave that is embedded in the passive data. In chapter 4, I presented the interferometry application to a surface passive dataset recorded during the hydraulic fracturing operation of a tight gas reservoir, that resulted in the successful extraction of dispersion properties for surface-waves. In applying interferometry, unlike existing studies that need hours or days of passive records to cross-correlate, here surface-waves were extracted by cross-correlating only a few minutes of passive records. This study showed that the choice of the pseudo-source location in passive dispersion analysis is important for the successful retrieval of surface-waves and their dispersion. Pseudo-source gathers and their corresponding dispersion images were better resolved when the pseudo-source location was close to the passive noise sources. When the dispersion analysis was applied to both passive and active data with a common acquisition, dispersion character (e.g.
velocity change with frequency) of the fundamental mode was observed to have the same behavior for both the active and passive data. However, for the higher mode surface-waves, the dispersion properties were extracted at different frequency ranges. As a result, using both passive and active data yielded surface-wave dispersive characteristics for a broader frequency range. An important outcome of this study was a sufficient understanding of the surface-wave properties in the $\tau - p$ and dispersion domains. This understanding led to the main idea of the next two chapters of this thesis, surface-wave suppression using $\tau - p$ transform.

Conventional noise suppression techniques in passive data are mostly stacking-based that rely on enforcing the amplitude of the signal by stacking the waveforms at the receivers and are unable to preserve the waveforms at the individual receivers necessary for estimating microseismic source location and source mechanism. In chapters 5 and 6 I introduced a technique, based on the $\tau - p$ transform, that effectively identifies and separates microseismic events from surface-wave noise in the $\tau - p$ domain. This technique is superior to conventional stacking-based noise suppression techniques, because it preserved the waveforms at individual receivers. Application of this methodology in Chapter 5 to two synthetic events, one with a uniform recorded polarity and one with a simplified double-couple source mechanism, showed substantial improvement in the signal-to-noise ratio. Additionally, in Chapter 6 applying this technique to an event with a more realistic double-couple source mechanism and a real microseismic event substantially increased the signal-to-noise ratios. Imaging of the processed field data also showed improved imaging of the hypocenter location of the microseismic source. Among the two approaches that I suggested in chapters 5 and 6 for unifying the polarities at the receivers, e.g. the cross-correlation approach (Chapter 5) and the semblance-based predicting approach (Chapter 6), the latter was more effective at unifying the polarities, especially for low signal-to-noise ratios.
7.2 Recommendations

The dispersion-curve inversion in this study was done for only one shot-gather obtained from seismic interferometry to demonstrate the feasibility of the method. Pseudo shot gathers can be generated for every receiver location followed by inversion of the dispersion curve to yield a 3D shear-wave velocity structure of the subsurface. It might be more accurate to even sort the pseudo-shot gathers into CMP gathers and perform dispersion-curve inversion on the individual CMP gathers. Since near-surface velocities can be azimuthally anisotropic, one could perform the same analysis for data from different azimuthal sectors to yield a 3D distribution of shear-wave velocity and its azimuthal anisotropy. The inverted shear-wave velocity model could be used in modeling surface-wave noise if the noise location and source signature are known. The modeled noise can subsequently be suppressed from data using an adaptive subtraction technique.

In implementing the noise suppression algorithm, the azimuthal information of the 3D data was disregarded by using a 2D $\tau-p$ transform. This resulted in averaging the waveforms and therefore, inaccuracy of the relative amplitudes of the microseismic events recorded at the receivers. I addressed this issue by performing a sector-wise noise suppression using the 2D $\tau-p$ transform that resulted in improving the waveform accuracy at the individual receivers. However, another alternative to possibly achieve more accurate waveforms is to perform a 3D $\tau-p$ transform which is not investigated here and should be explored further.

Moreover, the effectiveness of the sector-wise 2D $\tau-p$ transform in noise suppression strongly depends on the number of receivers included in each sector. This investigation was only qualitative (for example including more arms in the star-shaped array was suggested), yet, a quantitative study on the number of receivers as well as the receiver spacing for more effective noise suppression is a valid research subject. In other words, my research can lead to the important research topic of the acquisition design for surface-wave noise suppression in microseismic data.

The noise suppression approach presented here includes estimation of the radiation pattern for a double-couple source mechanism, which is directly tied to the fracture orientation.
However, two aspects are missing or simplified in this research. First, the fracture orientation is intended only to be used for optimal unification of the waveform polarities for a microseismic event and assumes a homogeneous medium with no variations of velocity due to heterogeneities or anisotropy. Therefore, for a future research a more realistic medium for the wave propagation can be considered. Second, we only apply the noise suppression to explosive (compressional) and double-couple source mechanisms, yet, there are microseismic events that are observed to be generated by non double-couple or tensile source mechanisms. Therefore, adopting our algorithm to include different types of source mechanism would be beneficial and result in more effective noise suppression.

Finally, the noise suppression algorithm suggested in this thesis involves user interaction and not fully automated. With the increased demand of real-time microseismic processing and analysis, developing an automated noise suppression algorithm would be more advantageous.
REFERENCES


APPENDIX A

MATHEMATICS OF INVERSE 2-D $\tau - P$ TRANSFORM

Here, we review the mathematical definition of the 2-D $\tau - p$ transform and summarize the derivation of the inverse $\tau - p$ transform suggested by Claerbout (1985) and Stolt & Weglein (2012). The 2-D forward $\tau - p$ transform ($\bar{U}(\tau, p)$) is defined as

$$\bar{U}(\tau, p) = \int_{-\infty}^{+\infty} U(x, t = \tau + px) \, dx,$$  \hspace{1cm} (A.1)

where $U(x, t)$ represents the data in the time-offset domain as a function of recording time ($t$) and source-receiver offset ($x$); $\tau$ represents the intercept of an event with the time axis and $p$ is the apparent slowness of the event. The 1-D Fourier transform of $\bar{U}(\tau, p)$ can be obtained by

$$\bar{U}(\omega, p) = \int_{-\infty}^{+\infty} \bar{U}(\tau, p) e^{i\omega\tau} \, d\tau,$$ \hspace{1cm} (A.2)

where $\omega$ represents the angular frequency. Substituting equation A.1 into A.2, we obtain

$$\bar{U}(\omega, p) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} U(x, \tau + px) e^{i\omega\tau} \, d\tau \, dx.$$ \hspace{1cm} (A.3)

Considering $t = \tau + px$, we transform the integration variable $d\tau$ to $dt$. Therefore equation A.3 becomes

$$\bar{U}(\omega, p) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} U(x, t) e^{i\omega(t - px)} \, dt \, dx.$$ \hspace{1cm} (A.4)
The 2-D Fourier transform of \( U(x, t) \) can be written as

\[
\hat{U}(k, \omega) = \int_{-\infty}^{+\infty} e^{-ikx} \, dx \int_{-\infty}^{+\infty} e^{i\omega t} U(x, t) \, dt. \quad (A.5)
\]

Comparing equations A.4 and A.5 and considering \( k = \omega p \), where \( k \) represents the wavenumber, we obtain

\[
\hat{U}(\omega, p) = \hat{U}(\omega p, \omega). \quad (A.6)
\]

Equation A.6 suggests that the \( \tau - p \) transform of the data \( U(x, t) \) followed by the 1-D Fourier transform is equivalent to the 2-D Fourier transform of the data.

Next, we apply a 2-D inverse Fourier transform to \( \hat{U}(k, \omega) \) and obtain

\[
U(x, t) = \frac{1}{(2\pi)^2} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-i\omega \tau} |\omega| \hat{U}(\omega, p) \, d\omega \, dp. \quad (A.7)
\]

Considering \( k = \omega p \), we transform the integration variable \( dk \) to \( dp \), and compute the Jacobian of transformation as

\[
dk = \det \begin{bmatrix} \frac{\partial \omega}{\partial \omega} & \frac{\partial k}{\partial \omega} \\ \frac{\partial \omega}{\partial p} & \frac{\partial k}{\partial p} \end{bmatrix} \, dp = \det \begin{bmatrix} 1 & p \\ 0 & \omega \end{bmatrix} \, dp = |\omega| \, dp. \quad (A.8)
\]

Then, we can re-write equation A.7 as

\[
U(x, t) = \frac{1}{(2\pi)^2} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-i\omega (t - px)} \hat{U}(\omega p, \omega) |\omega| \, d\omega \, dp, \quad (A.9)
\]

From equation A.6 we can substitute \( \hat{U}(\omega, p) \) for \( \hat{U}(\omega p, \omega) \). By considering \( \tau = t - px \) and re-arranging equation A.9, we obtain

\[
U(x, t) = \frac{1}{(2\pi)^2} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-i\omega \tau} |\omega| \hat{U}(\omega, p) \, d\omega \, dp, \quad (A.10)
\]

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Where \(|\omega|\tilde{U}(\omega, p)\) is a so-called rho-filter and can be represented by \(\tilde{U}(\omega, p)^{\rho_0}\). Substituting the rho-filter in equation A.10 and re-arranging this equation, we obtain

\[
U(x, t) = \frac{1}{(2\pi)^2} \int_{-\infty}^{+\infty} dp \int_{-\infty}^{+\infty} e^{-i\omega \tau} \tilde{U}(\omega, p)^{\rho_0} d\omega.
\]  
(A.11)

Considering that the 1-D inverse Fourier transform of \(\tilde{U}(\omega, p)^{\rho_0}\) is

\[
\tilde{U}(\tau, p)^{\rho_0} = \frac{1}{(2\pi)} \int_{-\infty}^{+\infty} e^{-i\omega \tau} \tilde{U}(\omega, p)^{\rho_0} d\omega,
\]  
(A.12)

we can re-write equation A.11 as

\[
U(x, t) = \frac{1}{(2\pi)} \int_{-\infty}^{+\infty} \tilde{U}(\tau, p)^{\rho_0} dp.
\]  
(A.13)

Comparing equations A.1 and A.13, we conclude that the inverse \(\tau - p\) transform in fact is similar to the forward \(\tau - p\) transform with a different integration variable, \(dx\), in the forward \(\tau - p\) and, \(dp\), in the inverse \(\tau - p\) transform. Also instead of applying the integration over \(\tilde{U}(\tau, p)\), one should integrate over \(\tilde{U}(\tau, p)^{\rho_0}\) and multiply the integration by a scaling factor \(1/2\pi\).
APPENDIX B

P-WAVE RADIATION PATTERN FOR AN ARBITRARY FAULT-PLANE

In this study, the only recorded component in the surface microseismic data is the vertical component and the source of the microseismic events is assumed to be a double-couple source. Therefore, we derive the P-wave radiation pattern due to double-couple forces. We consider that a fault is a plane and the activation of the fault occurs by a double-couple force which creates a shear-slip along the fault-plane. Mathematically, we can describe the fault-plane geometry with two vectors; a normal vector that is perpendicular to the fault-plane and a vector that represents the slip direction in the fault-plane (Aki & Richards, 2002; Stein & Wysession, 2003).

Note that the notations used here for derivation of the formulas are based on Landau & Lifschitz (1976). One can use two Cartesian systems to describe the arbitrary directions for the two normal and slip vectors in the 3-D space (Célerier, 1988). Figure B.1 illustrates these Cartesian systems; the initial system, $xyz$ and the secondary system $x'y'z'$, which is obtained by successive rotations of the initial system by angles $\phi$, $\psi$, and $\theta$. Vectors $\vec{\nu}$ and $\vec{d}$ are along the perpendicular to the fault-plane and the slip direction in the plane, respectively. We consider the initial fault-plane to be along $x - y$, and the directions of the normal to the fault-plane and the slip directions to be along $z$ and $x$, respectively. For every arbitrary fault-plane such as $x' - y'$ with the azimuth $\phi$ and the dip $\theta$, we can use the so called Euler relations to relate the arbitrary directions of the normal and slip vectors along $x'$ and $z'$, respectively, to their initial directions along $x$ and $z$. With Euler relations we can write the
components of \( \vec{\nu} \) and \( \vec{d} \) vectors as

\[
\nu_x = \sin \theta \sin \phi \\
\nu_y = -\sin \theta \cos \phi \\
\nu_z = \cos \theta
\]  

and

\[
d_x = \cos \psi \cos \phi - \cos \theta \sin \phi \sin \psi \\
d_y = \cos \psi \sin \phi + \cos \theta \cos \phi \sin \psi \\
d_z = \sin \theta \sin \psi,
\]

respectively. The P-wave radiation pattern, \( R_p \), due to a double-couple force applied to an arbitrary fault-plane can then be written as

\[
R_p \propto (\vec{\gamma}, \vec{\nu})(\vec{\gamma}, \vec{d})
\]  

(Aki & Richards, 2002), where "." denotes the dot product of the vectors; \( \vec{\gamma} \) is the longitudinal unit vector that connects the microseismic source \( \vec{s}(s_x, s_y, s_z) \) to a receiver \( \vec{r}(r_x, r_y, r_z = 0) \) at the surface and can be extracted by

\[
\vec{\gamma} = \frac{(\vec{r} - \vec{s})}{\sqrt{(r_x - s_x)^2 + (r_y - s_y)^2 + s_z^2}}
\]  

(B.4)
Figure B.1: Illustration of Euler angles; $\phi$ and $\theta$ are azimuth and dip of the fault-plane, respectively. $\psi$ denotes the slip angle and vectors $\vec{v}$ and $\vec{d}$ represent the normal to the fault and the slip vector, respectively.