Automatic First Break Detection by Spectral Decompostion Using Minimum Uncertainty Wavelets

A Thesis

Presented to

the Faculty of the Department of Mechanical Engineering

University of Houston

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in Mechanical Engineering

by

Sunil Kapur

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Sunil Kapur

Approved:

Chair of the Committee
Donald J. Kouri, Professor
Mechanical Engineering

Committee Members:

Jagannatha Rao, Associate Professor
Mechanical Engineering

Haleh Ardebili, Assistant Professor
Mechanical Engineering

Suresh K. Khator, Associate Dean
Cullen College of Engineering

Pradeep Sharma, Department Chair
Mechanical Engineering

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Abstract

Seismic Signal Processing can be effectively utilized to determine micro-seismic events. With the advances in hydraulic fracturing techniques, first break detection has become really important in locating micro-seismic events. The measured data collected gathers far more information than can be extracted by human operators and whose interpretation can consume a lot of time. The transformation in the computational efficiency suggests the involvement of computers in interpreting the measured data. We suggest a new method of first break detection that is based on time-frequency spectral decomposition method and utilizes the C_n Transform and the Super-Gaussian μ wavelets. We tested our method on lab data with various signals and first arrival time was determined. The results were compared to the manual detection and our method had an accuracy of 0.6 μ seconds. The results indicate that our method is robust and is successful in detecting the first arrival time automatically.

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Chapter 1 Introduction

Seismic data is recorded in the time-domain. There are different processing methods that can transform the data into a new domain, perform various manipulations and then use the inverse transform to return to the physical domain. One purpose of this procedure is to find a domain where the true signal can be separated more easily from noise (which is filtered or muted out). It is generally easier to characterize noise types and design filters with the data expressed in the transform domain. Filters are applied to data to alter it in a manner calculated to improve its quality in some way by removing noise.

Muting refers to the process of zeroing out unwanted transformed data samples to improve data quality and is therefore a crude filter. In theory, if no operation were performed the output would be identical to the input, however this is not always the case in practice because of approximations that may be made in the transform stages. Another important use of transforming time data to a transform domain is to separate different effects or components of the signal that may describe various aspects of the process under study. For example, wavelet transforms typically decompose a signal into various frequency sub-bands (e.g., low and high frequencies, along with frequency band interactions). The low frequencies generally describe gross, overall features and high frequencies add details.

Another reason for using transforms is computational efficiency. Certain operations on data can be more efficiently carried out in the transform domain, e.g., derivatives of data become multiplicative operations in the frequency domain and the computational effort can scale better with the size of the data set [1]. This is especially true since the advent of modern, high performance computers.

In refraction seismology, first break (or arrival time) detection has been applied to study the near surface low-velocity zone and determine the static corrections [1]. In recent years, with the advances in hydraulic fracturing techniques, first break detection has become a key to locating the micro seismic events.

We report a new method of automatic first break detection of P-waves and S-waves. The increasing importance of automation is due to the enormous amounts of data currently generated in seismic surveys. Our method is based on a time-frequency analysis of the seismic trace using minimum uncertainty (μ)-wavelets, in the minimum-phase form. We have tested our method on lab data with various diverse signals. Our method picks the first arrival time for lab data contaminated with both high and low amounts of noise with an accuracy of 0.6 μ - seconds. Our results indicated that our method is robust for automatically detecting the first arrival time.

1.1 Description of Signals

The data can be measured as a set of waveforms, a time series or images and the required information must be extracted from it. The data are called “signals". They provide us with very useful information; however, they are also accompanied by interfering noise. It has been found that the measured data has far more of information that can be extracted by the human operators and the sheer amount of data precludes its analysis by hand. This creates the need for creating computer-aided, interactive, and fully automatic methods for the processing of signals.

There can be a variety of signals. The signals can be both time and space dependent. Signals can be obtained as images from image sensors. The signals can also be a time sequence of recorded data. The fact that the signals can take so many diverse forms makes signal processing a very challenging field.

The signal processing can be analog or digital. The initial methods used analog signal processing. They are generally fast in operation but are limited by our ability to design circuits that describe the process of interest. However, the advancement in computer hardware and advanced languages has given impetus to digital signal processing. Digital signal processing is highly effective in performance and cost more importantly, it is also more flexible and accurate. The implementation of digital signal processing is reaching out to even more diverse areas and the trend is accelerating.

1.2 Heisenberg Uncertainty Principle

This is the main principle that differentiates quantum mechanics from classical mechanics. The Heisenberg Uncertainty Principle states that we cannot specify, exact values (eigenvalues) of a pair of non-commuting observables (e.g., position and momentum) simultaneously and places quantitative restrictions on their relative variances. It is desired to have a narrow width signal in seismic signal processing. But, according to Heisenberg's Principle, the bandwidth-duration product of any physical signal has to be greater than a minimum universal value. Consequently, it imposes a strong mathematical bound, which makes it impossible to create signals with arbitrarily narrow width simultaneously in both time and frequency. The essential origin of this principle is that quantum mechanics possesses the mathematical structure of a Hilbert space [2]. The transformation between, e.g., the position representation of the vector space and the canonically conjugate momentum representation is simply a Fourier transform and was utilized in previous work on this topic. We are utilizing a generalization of this concept which has led to the C_n-transform in this research [14].

1.3 Wavelets

A wavelet is a term that has been used in several ways in seismology. From a less mathematical point of view, it is used for a short time series (typically less than 100 samples) which is used to represent, for example, the acoustic wave source function. In mathematics, a wavelet is a pulse or signal that is well-localized both in the time and the frequency domains. This localization is quantitatively measured by the standard deviation of the signal, Δt, in the time domain, multiplied by $\Delta \omega$ in the frequency domain. Heisenberg's uncertainty principle says that

$$\Delta t \Delta \omega \geq (1/2). \tag{1.1}$$

The minimum value of 1/2 is satisfied by a Gaussian signal. This fact is fundamentally related to the fact that the Fourier transform of a Gaussian in time to frequency also is a Gaussian. In recent, unpublished research of Williams, Bodmann and Kouri [14], it was proved that other wavelets can be based on "Super-Gaussians", one case of which is given by

$$\phi_2^0(t) = e^{-t^4/4}. \tag{1.2}$$

They are form-invariant under a generalized transform, denoted as the C_n transform (n =1,2,....) [14]. When n = 1 , we have the standard Gaussian. The wavelets associated with $\phi_n(t)$ are explicitly in section 3.1 of this thesis.

The signal can be studied as a time series in the time domain or in the frequency domain as an amplitude or phase spectrum. For any amplitude spectrum there are an infinite number of time domain wavelets which can be constructed by varying the phase spectrum. There are two special types of phase spectra of specific interest - Zero Phase and Minimum Phase as shown in Figure 1.1.

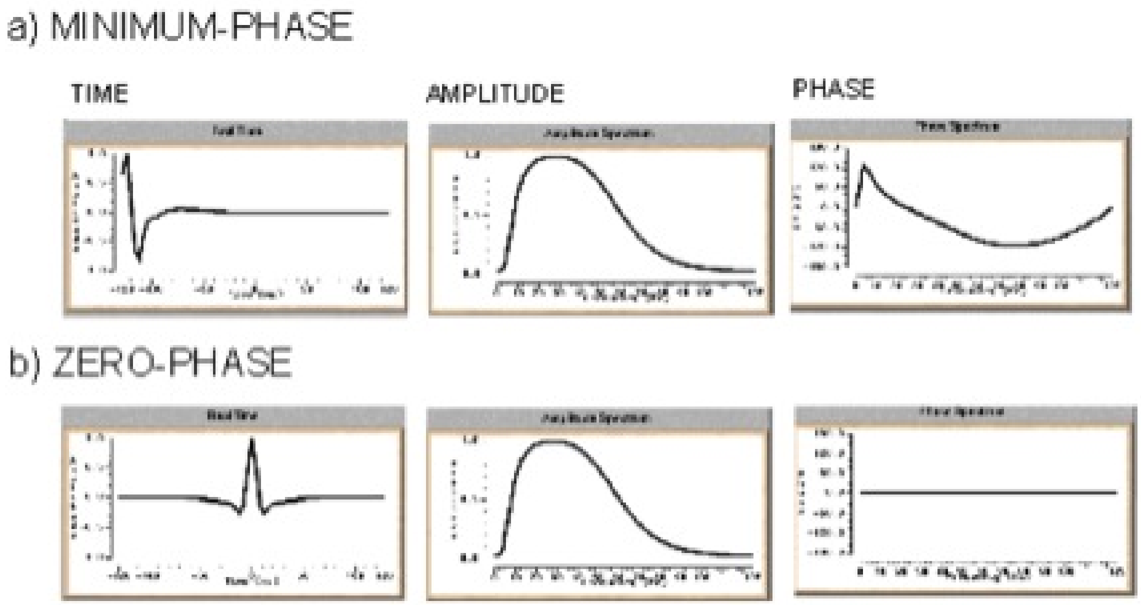

Figure 1.1. Types of Muwavelets

The minimum phase wavelet has a short time duration and a concentration of energy at the start of the wavelet. It vanishes before the time equal to zero (it is causal). An ideal seismic source would be a spike (maximum amplitude at every frequency), but the best practical one would be minimum phase. It is quite common to convert a given wavelet source wavelet into it's minimum phase equivalent since several processing stages (e.g., predictive deconvolution) work best by assuming that the input data is minimum phase.

The maximum phase wavelet is the time reverse of the minimum phase and at every point the phase is greater for the maximum than the minimum. All other causal wavelets are strictly speaking mixed-phase and will be of longer time duration. The convolution of two minimum phase wavelets is minimum phase.

The zero-phase wavelet is of shorter duration than the minimum phase equivalent. This wavelet is symmetrical with a maximum at time zero (non-causal). The fact that energy arrives before time zero is not physically correct but the wavelet is useful for increased resolving power and ease of picking reflection events (peak or trough).

The convolution of a zero-phase and minimum phase wavelet leads to mixed phase (because the phase spectrum of the original minimum phase wavelet is not the unique minimum phase spectrum for the new modified wavelet) and should be avoided.

1.4 Difficulty with the Hilbert Transform

We use Hilbert Transform to compute the minimum phase wave from a zero phase wave, which is basically an integral formula. So, when we use log(abs(Fourier transform)), the log function blows up at the zeros of the transformation. So, to avoid getting vague results, we insert a stability constant to remove zeros. The stability constant is defined as ϵ and results in log(abs(Fourier transform) + ϵ), where ϵ is small.

1.5 Singular Value Decomposition Method

We utilized Singular Value Decompostion Method (SVD) in determining the pseudo inverse. A detailed SVD method is presented in [13]. It helped in understanding the concept of SVD and in implementing the same computationally. There are a lot of applications of SVD in linear algebra and linear systems and Singular Value Method is a very effective tool in the modern day mathematics.

Singular value decomposition (SVD) can be looked at from three mutually compatible points of view. On the one hand, we can see it as a method for transforming correlated variables into a set of uncorrelated ones that better expose the various relationships among the original data items. At the same time, SVD is a method for identifying and ordering the dimensions along which data points exhibit the most variation. This ties in to the third way of viewing SVD, which is that once we have identified where the most variation is, it's possible to find the best approximation of the original data points using fewer dimensions. Hence, SVD can be seen as a method for data reduction.

As an illustration of these ideas, consider the 2-dimensional data points in Figure 1.2. The regression line running through them shows the best approximation of the original data with a one-dimensional object. It is the best approximation as it is the line that minimizes the distance between each original point and the line.

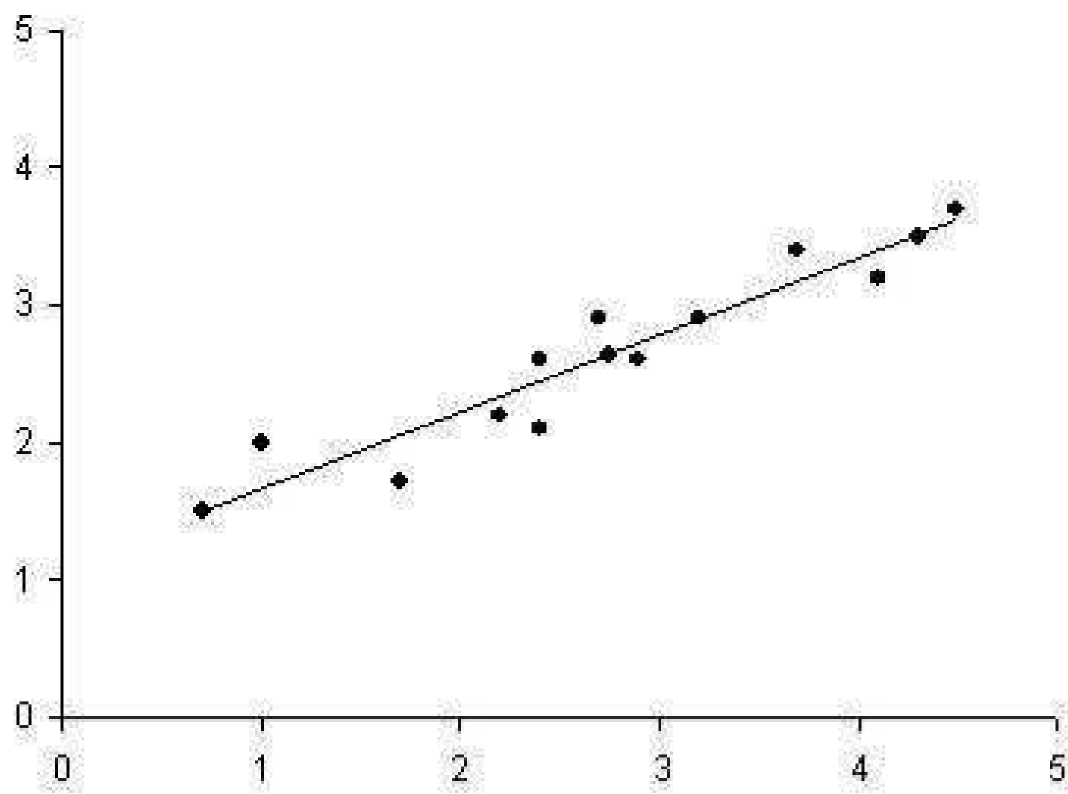

Figure 1.2. Best-fit regression line reduces data from two dimensions into one.

If we drew a perpendicular line from each point to the regression line, and took the intersection of those lines as the approximation of the original data point, we would have a reduced representation of the original data that captures as much of the original variation as possible. Notice that there is a second regression line, perpendicular to the first, shown in Figure 1.3. This line captures as much of the variation as possible along the second dimension of the original data set. It does a poorer job of approximating the original data because it corresponds to a dimension exhibiting less variation to begin with. It is possible to use these regression lines to generate a set of uncorrelated data points that will show subgroupings in the original data.

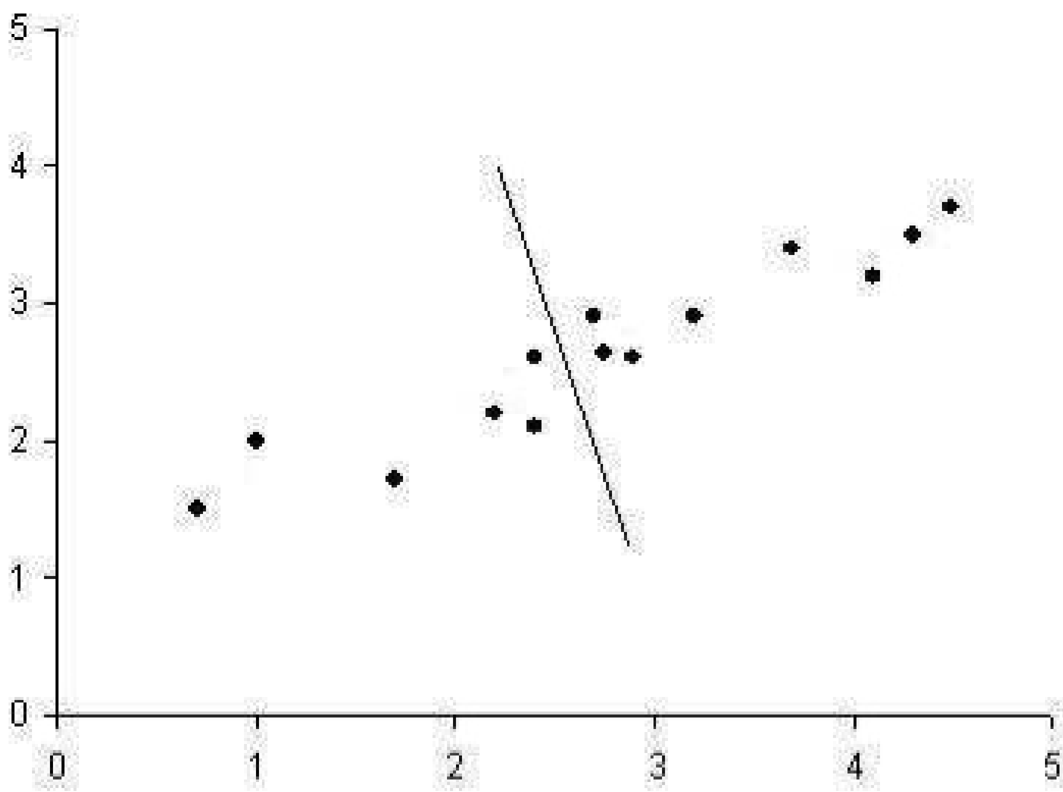

Figure 1.3. Regression line along second dimension captures less variation in original data.

These are the basic ideas behind SVD: taking a high dimensional, highly variable set of data points and reducing it to a lower dimensional space that exposes the substructure of the original data more clearly and orders it from most variation to the least. What makes SVD feasible is that you can simply ignore variation below a particular threshold to massively reduce your data but be assured that the main relationships of interest have been preserved.

Chapter 2 Review of Previous Work

There are two kinds of first arrival picking methods, one which is applied in the time domain and the other which is applied in the frequency domain. Several methods have been suggested for first arrival picking which are applied to the time domain signal, including the multi-window algorithm [8] and the short-term average/ long-term average method [6]. In the time domain picking method, the μ-wavelets are cross-correlated with each trace and the maximum indicator of the time shift are collected. And since the minimum phase μ-wavelet is causal, the point of maximum cross correlation corresponds to the first arrival time. However, it doesn't work as well as desired, in part because in the time domain, it is difficult to isolate the noise from the signal.

In the frequency domain, it has been observed that at the onset of a micro-seismic event, the high frequency component of the micro seismic traces increases dramatically [5]. The frequency characteristics of a trace can be analyzed and optimal temporal and frequency localization can be performed which can yield accurate results. However, the μ-wavelets are constrained by the Heisenberg uncertainty product [2], so spectral decomposition technique can be used to enhance the temporal and frequency resolution [3].

Our first break detection method is based on a time-frequency domain approach. It has been seen that in zero-phase wavelets, the signal is non-causal and it leads to pre-arrival energy leaks and we don't obtain the true first arrival time. So, in order to avoid this, we incorporate the minimum phase wavelets that are achieved by Hilbert transforming the original μ-wavelets into a causal form, i.e., the minimum phase wavelets.

In the previous study performed, μ-wavelets were based on Fourier transforms [1]. The minimum phase form was used. The results achieved in the lab data test yielded an accuracy of 0.5 μs compared with the manual detection results. We have used the Super-Gaussian μ-Wavelets determined using the C_n Transform. On comparing the results with the fourier transform [1], with our results for the C_n transform at n = 1, we find them to be the same.

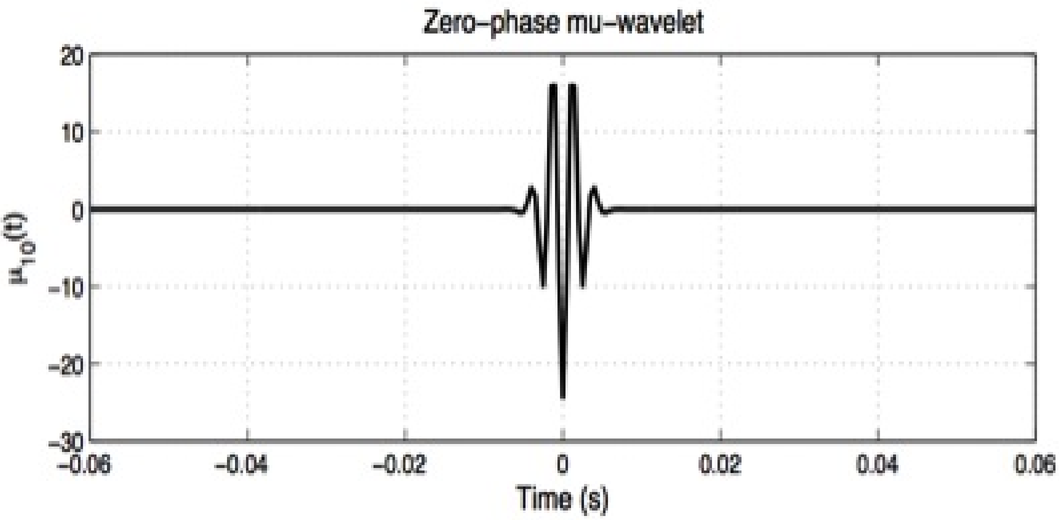

Figure 2.1. Zero Phase wavelet for fourier transform[1].

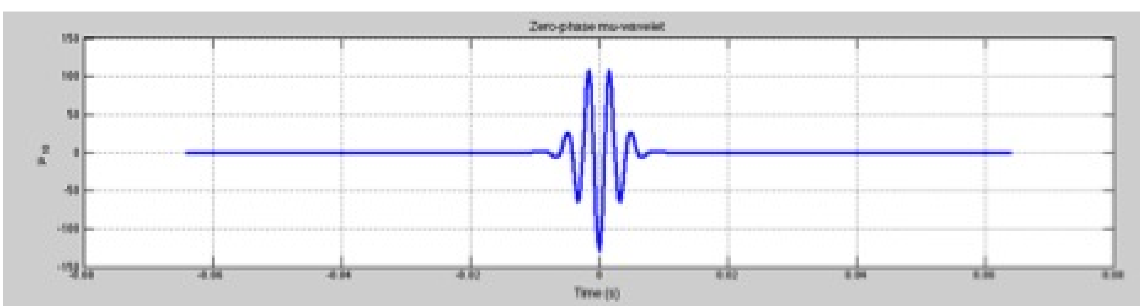

Figure 2.2. Zero Phase wavelet for C_n Transform at n = 1.

Now, it was desired to determine the results for n = 2. We have used a time-frequency decomposition of the signal using the μ-wavelets. Our first arrival indicator uses the maximum of the power mean as computed from the time-frequency record.

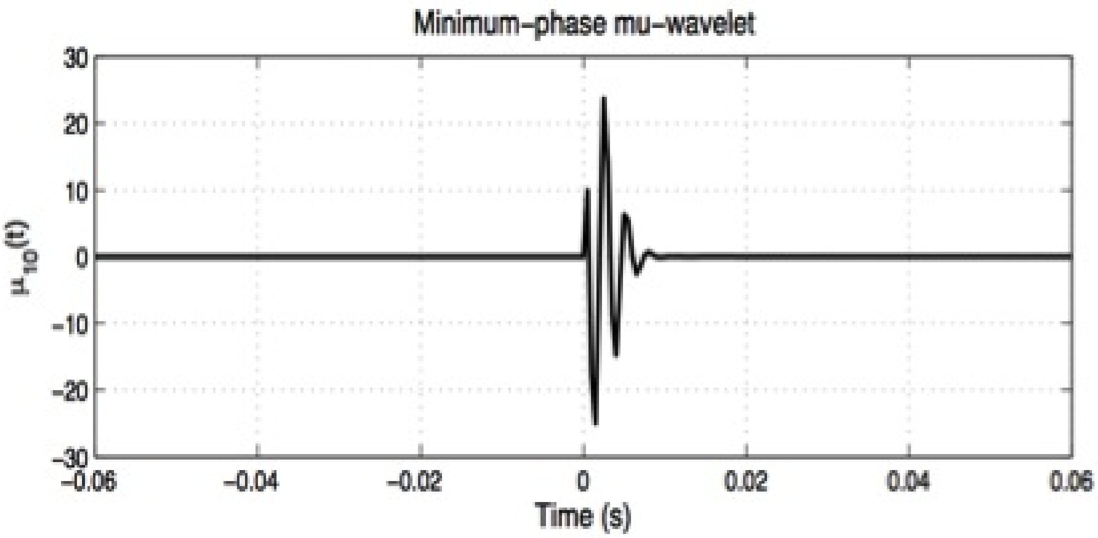

Figure 2.3. Minimum Phase Wavelet for fourier transform[1].

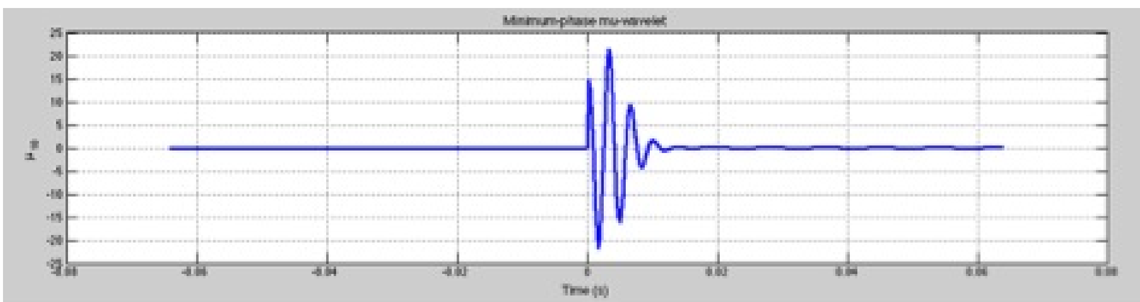

Figure 2.4. Minimum Phase wavelet for C_n Transform at n = 1.

In the figure 2.5, the first arrival indicator is calculated using a signal and a fourier transform. The first arrival was at 0.2228 ms [1] and the result through manual detection is 0.22238 ms. So, the accuracy was up to 0.5 μ seconds.

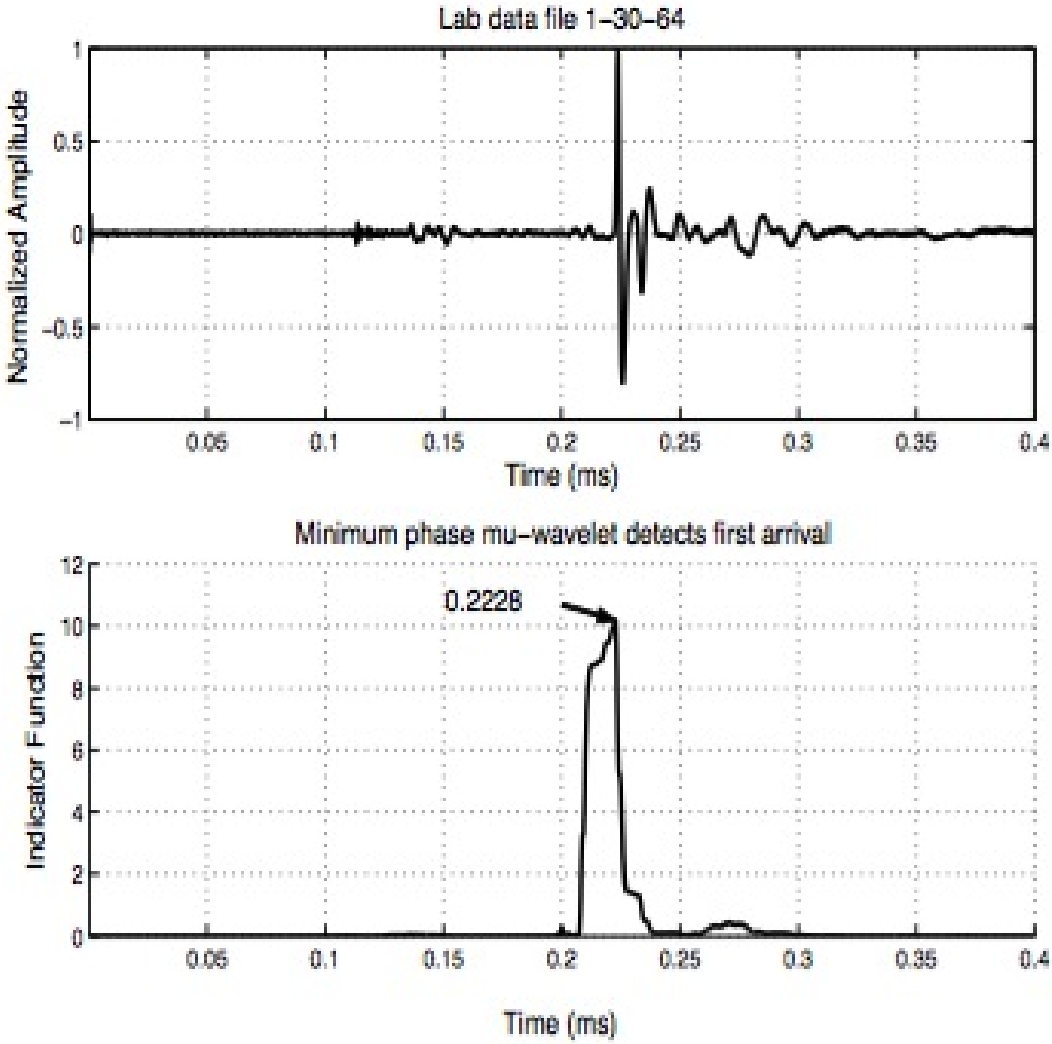

Figure 2.5. Arrival Time using the Fourier Transform, $t_s = 0.2228ms$ [1].

Chapter 3 Analysis of the Problem

We desired to develop a new automatic detection method and then compare the results with the manual detection method. We used Super Gaussian μ wavelets and utilized the C_n transform to obtain an expression for the μ wavelets in the frequency as well as in the time domain.

The signals are collected in the time domain but due to limitations of analyzing them in the time domain, we performed a transform and converted them to the frequency domain and then the analysis was performed. The μ wavelets obtained are in the zero phase which has its own limitations as discussed before. So, we converted them to minimum phase wavelet. The minimum phase wavelet being causal, invertible and has a finite energy helped in overcoming the limitations which are faced using zero phase wavelets. The different convolution methods also work better on the minimum phase wavelets.

3.1 Supergaussian μ-Wavelets and the C_n Transform

The Super Gaussian μ wavelets in the frequency and time domains are defined in the equation 3.4 and equation 3.5 respectively [14]. Also, the μ-wavelets are plotted for n = 1 for the zero phase and the minimum phase in the figure 3.1 and figure 3.2 respectively. The results identical to those obtained with the Fourier transform [1]. For n = 2, the zero phase as well the minimum phase μ-wavelets are plotted in the figure 3.3 and figure 3.4 respectively.

The C_n transform of a function f is, in general, given by

$$C_n(f(t))(\omega) = \int_{-\infty}^{\infty} C_n(\omega t) f(t) dt, \tag{3.1}$$

where $C_n(\omega t) = D_n(\omega t) + iB_n(\omega t)$.

$$D_n(\omega t) = \frac{1}{2}|\omega t|^{n-\frac{1}{2}} J_{-1+\frac{1}{2n}}(\frac{|\omega t|^n}{n}), \tag{3.2}$$

and B_n is given by the negative Hilbert Transform of D_n. In the frequency domain, the wavelets have the form

$$\phi_n^{(j)}(\omega) = \frac{1}{j!}(\frac{\omega^{2n}}{2n})^j e^{-\frac{\omega^{2n}}{2n}}, \tag{3.3}$$

so that their sum (over j) is an almost ideal approximation to the ideal window. These wavelets can be recognized to satisfy the following expression:

$$\phi_n^{(j)}(\omega) = (-\frac{\partial}{\partial\alpha})^j e^{-\alpha^{\omega^{2n}/2n}}|_{\alpha=1}. \tag{3.4}$$

If the corresponding C_n transform is taken, the following expression for the μ wavelets in the time domain results

$$\phi_n^{(j)}(t) = (-\frac{\partial}{\partial\alpha})^j (\alpha^{1/2n} e^{t^{2n}/2n\alpha})|_{\alpha=1}. \tag{3.5}$$

This follows directly from

$$C_n(f(\alpha t))(\omega) = \frac{1}{\alpha} C_n(f(t))(\frac{\omega}{\alpha}). \tag{3.6}$$

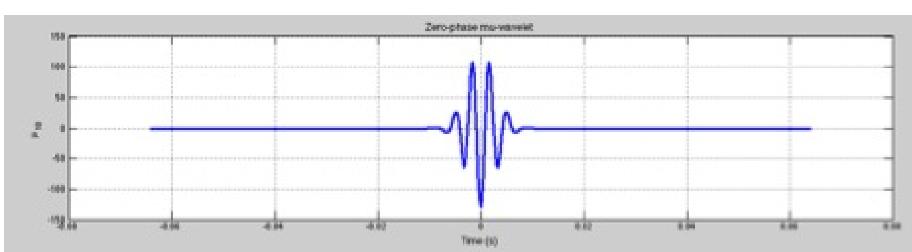

Figure 3.1. Zero Phase wavelet for C_n Transform at n = 1 (Same as standard Fourier transform).

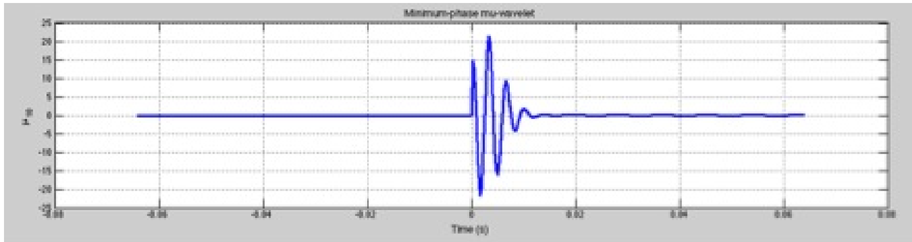

Figure 3.2. Minimum Phase wavelet for C_n Transform at n = 1 (Same as standard Fourier transform).

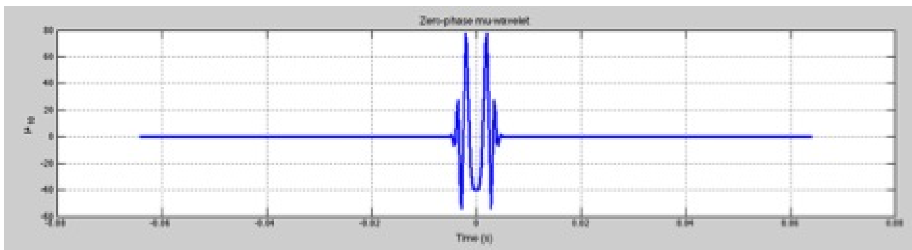

Figure 3.3. Zero Phase wavelet for C_n Transform at n = 2.

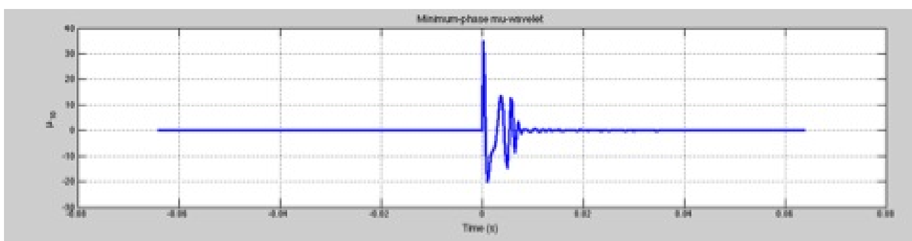

Figure 3.4. Minimum Phase wavelet for C_n Transform at n = 2.

It is extremely interesting to observe the minimum phase wavelet for n = 2 compared to the Gaussian-based (n = 1) minimum phase wavelet. One desires that the maximum occur at t = 0 (in order to identify the first arrival), the n = 2 minimum phase wavelet satisfies this much better than the n = 1 case. We will see that this results in a much better indicator of the first arrival.

3.2 Algorithm

A linear combination of the μ-wavelets can be expressed as :

$$S(\tau) = \sum_{l=0}^{N} C_n^{(l)}(\tau)\phi_n^{(l)}(\tau). \tag{3.7}$$

Now, we carry out the following steps to obtain the time - frequency decomposition.

Step 1 : Crosscorrelate the analysis μ-wavelet $\phi_n^{(l')}(t)$ with both sides and we obtain

$$\phi_n^{(l')}(t) \otimes S(t) = \phi_l^{(l')}(t) \otimes \sum_l C_n^{(l)}\phi_n^{(l)}(t), \tag{3.8}$$

$$\phi_n^{(l')}(t) \otimes S(t) = \sum_l C_n^{(l)}\phi_n^{(l')}(t) \otimes \phi_n^{(l)}(t), \tag{3.9}$$

where

$$g(t) \otimes f(t) = \int_{-\infty}^{\infty} g(t+\tau)f(t)dt, \tag{3.10}$$

Now, Let's define

$$d_m(\tau) = \int_{-\infty}^{\infty} \phi_n^{(l')}(t+\tau)S(t)dt, \tag{3.11}$$

$$X_{mn}(\tau) = \int_{-\infty}^{\infty} \phi_n^{(l')}(t+\tau)\phi_n^{(l)}(t)dt. \tag{3.12}$$

The equation can be written as

$$d_m(\tau) = \sum_l X_{mn}(\tau)C_n^{(l)}, \tag{3.13}$$

and we can obtain the coefficients $C_n^{(l)}$ by using

$$C_n^{(l)}(\tau) = \sum_l X_{mn}^{+}(\tau)d_m(\tau), \tag{3.14}$$

where X^{+}_{mn} is the pseudo inverse of X_{mn} and can be obtained by the Singular Value Decompostion Method.

Step 2 : We obtain the time-frequency representation of the signal by multiplying the coefficients with the C_n Transform of the μ Wavelets,

$$S(\tau,\omega) = \sum_{l} C_n^{(l)}(\tau)\phi_n^{(l)}(\omega), \tag{3.15}$$

where $\phi_n^{(l)}(\omega) = C_n^{(l)} T(\phi_n^{(l)}(t))$.

Step 3 : Now , we define the power spectrum $P(\tau,\omega) = S^2(\tau,\omega)$, of the time-frequency form of the signal and then integrate it over frequency at various time τ to define the first break indicator function , $f(\tau)$,

$$f(\tau) = \int S^2(\tau,\omega)d\omega. \tag{3.16}$$

Step 4 : The next step is to apply a peak-picking algorithm to find the peak, and denote them as an identifier for the first arrival. We specify a potential region of the first arrival. In the potential region, we neglect one other point and then we apply the Hermite Distributed Approximating Functional (HDAFs) to filling the neglected points [7]. This effectively helps in obtaining a less noisy indicator function at the potential region. And, we find the maximum of all the points in the potential region as our indicator. Thus we obtain arrival indicator for the wave arrival.

Chapter 4 Results and Discussion

The experiment data was done for an S-wave source. The original sampling frequency was 50 MHz. We re-sampled the data with sampling frequency of 5 MHz for our test. The seismic trace was gathered by stacking 64 signals in figure 4.2 and figure 4.4. But the seismic trace in figure 4.6 was not stacked. The signals in figure 4.4 and 4.6 are noisier than that of figure 4.2, as we can see from both the original signals and the indicator functions. Our automatic time arrival detections for the three signals are very close to each other and to the actual arrival time by manual detection method, which is 0.22238 ms, our automatic time arrival detection has error of less than 0.6 μ-seconds. This illustrates the accuracy of our method.

We tested the μ-wavelet for three different lab data. The Manual Detection Value was 0.22238 ms. We detected the first arrival time and we got the first arrival value as 0.2226 ms and 0.2230 ms for n = 1 and n = 2 respectively. We utilized the concept of minimum phase uncertainty wavelets and performed C_n-transform to obtain the μ-wavelets in the time domain and the frequency domain.

Initially, the signal was collected in the time domain and then, we transformed it in the frequency domain, as it got easier to be separated from noise effects and then we performed the singular value decomposition method to obtain the pseudo-inverse. After obtaining the pseudo-inverse, we calculated the power spectrum and utilized the HDAFs to fill the points which really helped in reducing the noise effects in the potential region. And, then we calculated the maximum of all the points in the potential region.

The results are extremely interesting when we compare the relative peak heights for the n = 1 and n = 2 cases. In the n = 1 Gaussian based μ wavelets, the maximum of the indicator function is only slightly higher than other peaks nearby. By contrast, in the n = 2 Super-Gaussian based wavelets yield an extremely large contrast between the indicator function height at the arrival then any other times in the plots. We conclude that the resolving power of the Super-Gaussian wavelets is much superior.

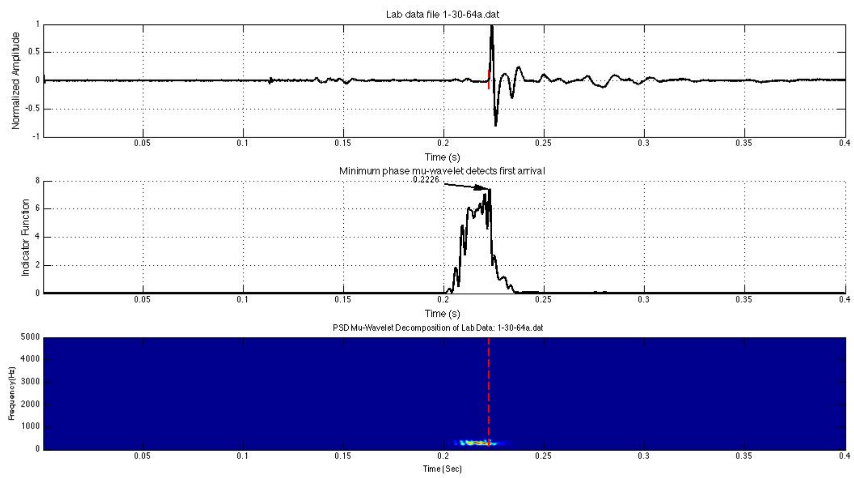

Figure 4.1. The First Indicator Function for a stacked seismic trace of gain +30dB , Arrival Time t = 0.2226 ms for n = 1.

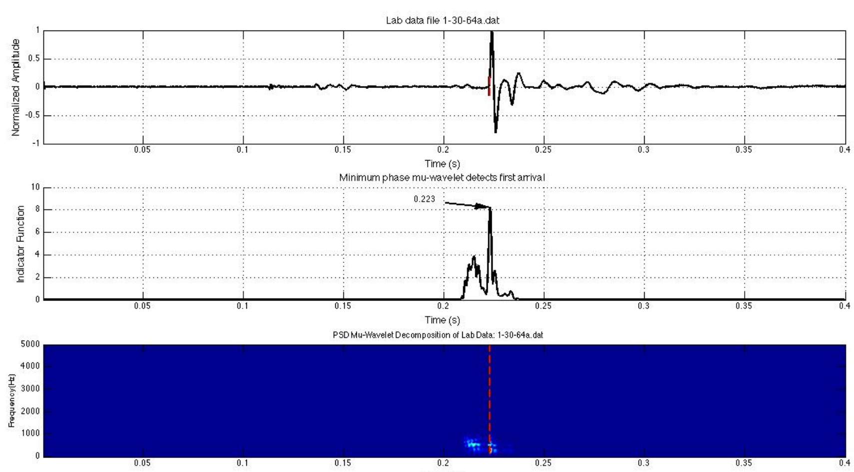

Figure 4.2. The First Indicator Function for a stacked seismic trace of gain +30 dB , Arrival Time t = 0.2230 ms for n = 2.

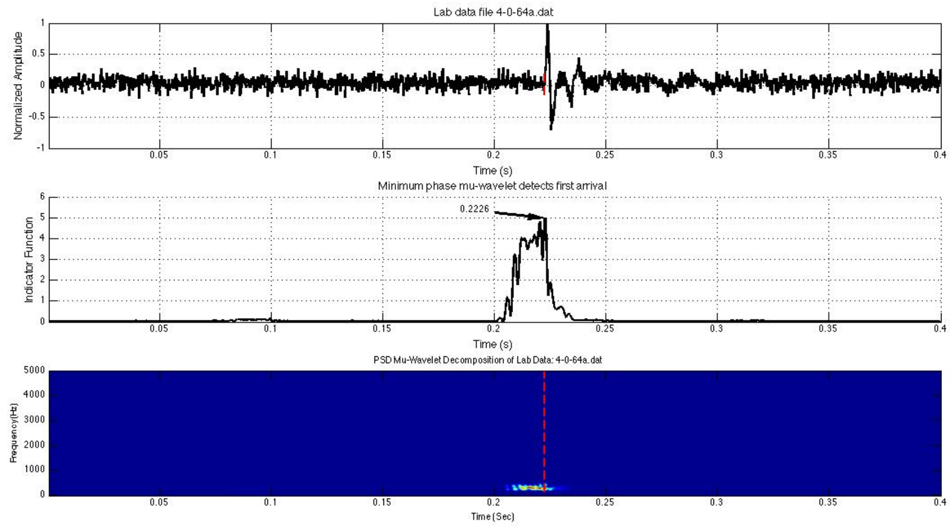

Figure 4.3. The First Indicator Function for a stacked seismic trace of gain 0 dB , Arrival Time t = 0.2226 for n = 1.

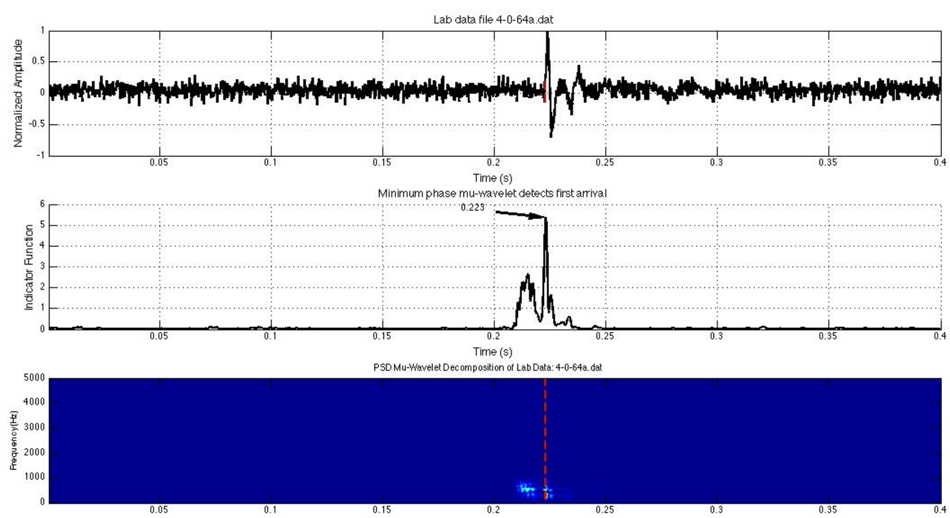

Figure 4.4. The First Indicator Function for a stacked seismic trace of gain 0 dB , Arrival Time t = 0.2230 ms for n = 2.

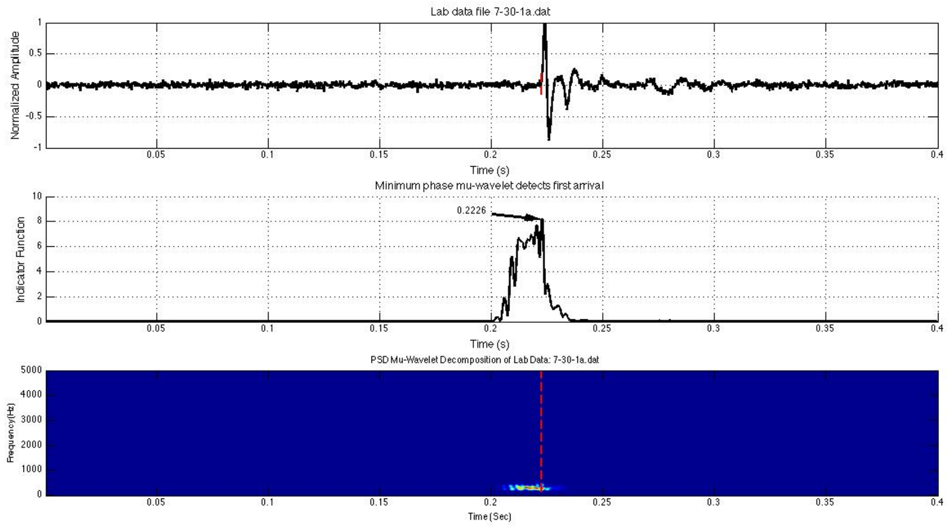

Figure 4.5. The First Indicator Function for one seismic trace of gain +30dB , Arrival Time t = 0.2226 ms for n = 1.

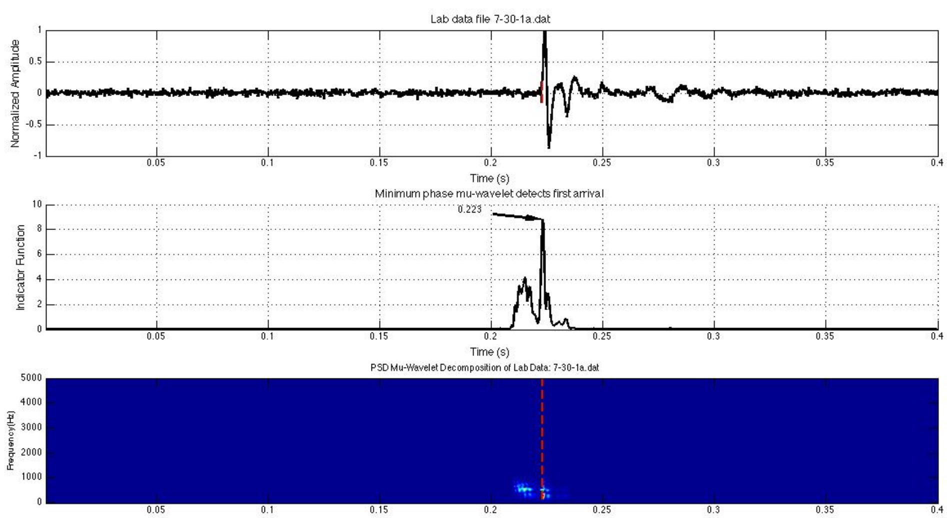

Figure 4.6. The First Indicator Function for one seismic trace of gain +30dB , Arrival Time t = 0.2230 ms for n = 2.

Chapter 5 Summary and Conclusions

We proposed a new method for the automatic first break detection. We calculated the first arrival for n = 1 and n = 2 using the Super Gaussian μ - Wavelets and the C_n-Transform. The method is based on a time-frequency analysis of the seismic trace using minimum uncertainty (μ)-wavelets. The perfomance of this method was tested on lab data and three different signals were used.

The results acheived were converged and we calculated at n = 1 and n = 2. In the case of n = 1, we got accuracy of less than 0.5 μ-seconds as was suggested in the case of fourier transform[1]. In the case of n = 2, we got an accuracy of 0.6 μ-seconds. The Sampling Frequency used was 5000 Hertz for the test. The manual detection result was 0.22238 ms and we got 0.2226 ms in the case of n = 1 and 0.2230 ms in the case of n = 2 by using C_n-Transform.

We tested the method on three different signals with different noise levels contamination and we got precise results in all the cases. We used minimum phase wavelets instead of zero phase wavelets and it helped in achieving an higher degree of accuracy due to the much higher resolution of the indicator function for the Super-Gaussian based wavelets. Hence, it can be interpreted that our method is robust and accurate for the automatic first break detection by spectral decomposition.

Chapter 6 Applications

There has been enormous growth in the field of signal processing in the past decade. As, the computational power increased, it helped in reducing the costs involved in signal processing. This research can find it applications in diverse areas of Seismic Signal Processing. The concept of wavelets can be utilized to solve differential equations and can process the seismic data. It can be utilized in the oil and gas industry for exploration activities. It can also be used in determining the seismic activity in the Earth Crust for predicting natural calamities like earthquakes and volcanoes and hence can help in reducing the loss to life and property.

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