Chapter 2

A Fractal-Based Algorithm For Detecting First Arrivals on Seismic Traces

In prediction of a successive analysis of model and field seismic data the problem related to the accurate automatic picking of seismic first arrivals has been tackled. In this chapter a new algorithm is proposed which detects the presence of signal by analysing the variation in fractal dimension along the trace. A change in dimension is found to occur close to the transition from noise to signal plus noise, that is the first arrival. The algorithm has been tested on real data sets with varying signal-noise-ratios and the results compared to those obtained using previously published algorithms. With an appropriate tuning of its parameters, the fractal-based algorithm proved more accurate than all these other algorithms, especially in the presence of significant noise. The fractal method proved able to tolerate noise up to 80% of the average signal amplitude. However, the fractal-based algorithm is considerably slower than the other and hence is intended for use only on datasets with low signal-noise ratios. The conten of this chapter has been recently accepted for publication in GEOPHYSICS.

2.1 Introduction

The accurate determination of the travel-time of seismic energy from source to receiver is of fundamental importance in seismic surveying. This is particularly the case with seismic refraction and tomographic surveys where the travel-times, usually of first arrivals, are used to determine the seismic-velocity structure of the sub-surface. To improve efficiency and speed of interpretation of such data it is common to use an automated technique for detecting seismic events and several such algorithms have been published. As larger and larger data sets are now being used for such interpretations these automatic methods of detecting the seismic arrivals have become an essential part of the precessing of the seismic data.

Fundamentally, the detection of the first-arriving seismic data reduces to determining the time when the seismic trace ceases to be composed entirely of noise and starts to also include the seismic signal. When such an operation is carried out manually, a subjective decision is made based on the change in the nature of the trace in terms of amplitude and/or frequency and/or phase both within the trace itself and also relative to its neighbours. However, what is a relatively simple operation for the human eye and brain is much more difficult to define mathematically and translate into an algorithm.

Several methods for locating first break have been published [7, 18, 9, 5, 16]. Most of the methods are based on identifying a particular property of that part of the trace where the first arrival occurs. Some methods also rely on comparison of the trace with its immediate neighbours. The different methods proposed to detect first arrivals will give slightly different arrival times depending on exactly what property of the trace they are based on, but in general are extremely effective provided there is an adequate signal-to-noise ratio. However, in a situation of very low signal-to-noise ratio their accuracy may be seriously affected.

In this paper a new method of picking seismic first arrivals in noisy datasets based on the change in fractal dimension within the trace associated with the advent of the signal is proposed. Since fractal dimension can be thought of as measuring the 'roughness', i.e the overall shape, of the trace, the algorithm automatically simulates the way the human brain identifies the first arrival.

2.2 Calculation of Fractal Dimension

Since its original introduction by Mandelbrot [13] the concept of fractals and fractal dimension has found widespread applications in many fields including the earth sciences. For the definition and an extensive description of the concepts behind fractals the reader is referred to [11, 14, 15, 8], while their use in geophysics is described in [21] and [20].

A number of different methods have been proposed to calculate the fractal dimension of a curve, or in this case a seismic trace. Two methods have been employed in this study: the 'structured walk technique' or 'divider method' [11, 10] and the 'Hurst method' [19]. The two methods represent two different class of techniques for measuring fractal dimension. The 'divider method' gives a measure of the Hausdorff dimension that is related to the geometry of the object under analysis, while the 'Hurst method' is an example of stochastic techniques, and it gives a measure of the statistical relationship between the dependent and the independent variables. It should be noted that these two techniques actually measure two different phenomena and they are not expected to give the same dimension when applied to the same data set [3]. There has been some discussion in the literature as to the relative merits of different methods of measuring fractal dimension [12] and in particular to the appropriate use of the 'divider method' for self-affine curves, e.g. time-series data such as seismic traces [17, 2]. This discussion is beyond the scope of this paper, and here the term 'fractal dimension' is used for the parameter obtained using either method. Moreover, our method does not rely on the absolute value of the fractal dimension of a given part of the seismic trace, but rather on the relative variation in fractal dimension along the trace. From this point of view, a seismic trace is considered simply as a digitised curve, along which the relative variation of geometrical and statistical characteristics are analysed independent of the absolute scaling of the X and Y axis.

2.2.1 Calculation of fractal dimension using the divider method

The basis of the divider method is to measure the length of the curve by approximating it with a number of straight-line segments, called 'steps' (Figure 2.1).

The calculated length of the curve is the product of the number of steps andthe length of the step itself. As the step size is decreased, the straight-line segments can follow the curve more closely, smaller-scale structure becomes more significant, and the calculated length of the curve increases. If the data follow a fractal model we have:

$$L(r) \propto r^{(1-D)} \tag{2.1}$$

where L is the curve lenght, r is the step lengh and D is the fractal dimension. Plotting the logarithm of the step length versus the logarithm of the corresponding curve length, a Mandelbrot-Richardson plot is obtained (Figure 2.1d). The slope of a line fitted to these points is related to the degree of complexity of the curve being analysed. This slope is related to the fractal dimension by the equation:

$$D = 1 - S \tag{2.2}$$

where D is the fractal dimension, and S the slope of the line /citeken86. The slope of the Mandelbrot-Richardson plot is equal to, or less than, 0. Thus, in the case of a curve such as the seismic trace, the fractal dimension is between 1 and 2.

Figure 2.2 is a typical Mandelbrot-Richardson plot obtained from analysis of a seismic trace. Note that the points do not define a single straight line segment, instead four segments (A, B, C and D in the figure) are seen. This is due to the fact that the seismic trace is not a perfect self-similar fractal. Also, the imperfect behaviour of the seismic trace is related to its representation as a series of discrete samples. The accuracy of the presentation of the trace is limited by the sampling interval and dynamic range of the digitiser. If the calculation of the length of the curve is performed with a too long step the main structure of the line cannot be described giving rise to the flat section (D) in Figure 2.2. When the step size is much less than the sample interval

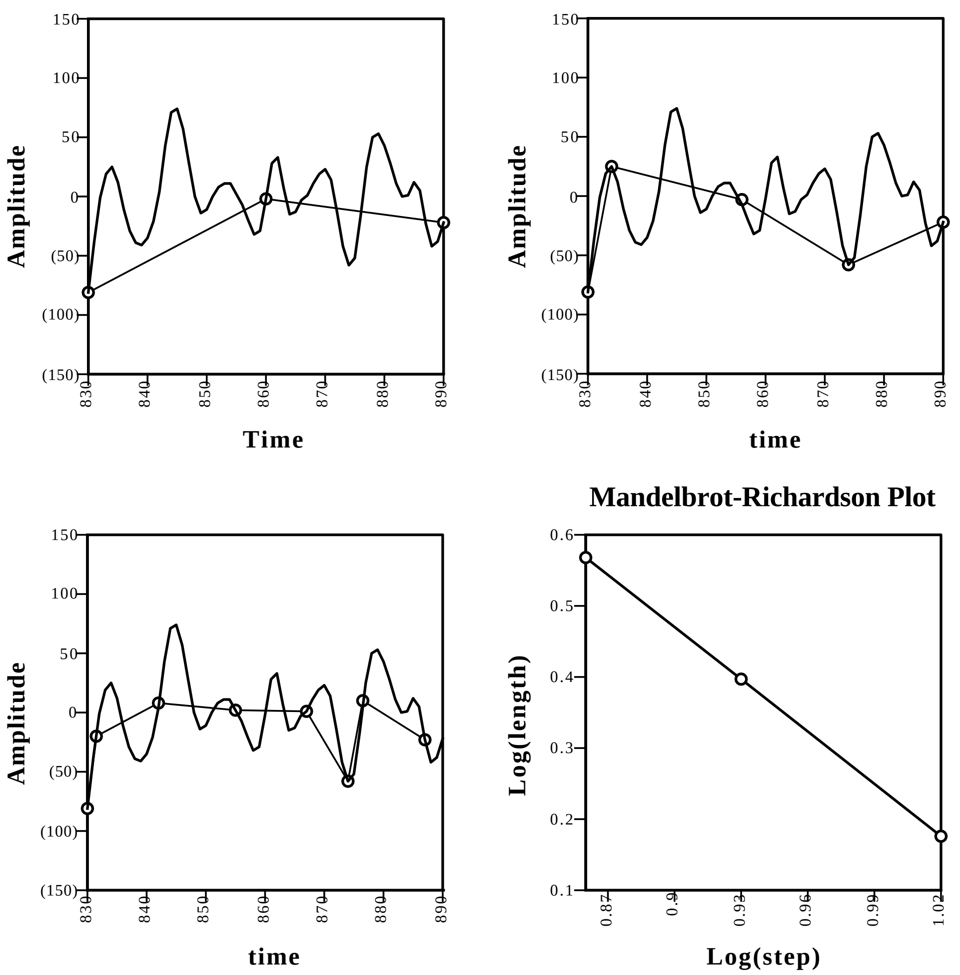

Figure 2.1: Calculation of fractal dimension using the 'Divider method'. The curve is approximated with a number of straight-line segments, called 'steps'. With a long step only the main structures The logarithm of the step length versus the logarithm of the corresponding step length is plotted (a Mandelbrot-Richardson plot). The slope of the line fitting the points is a measure of the degree of complexity of the curve and is related to its fractal dimension.

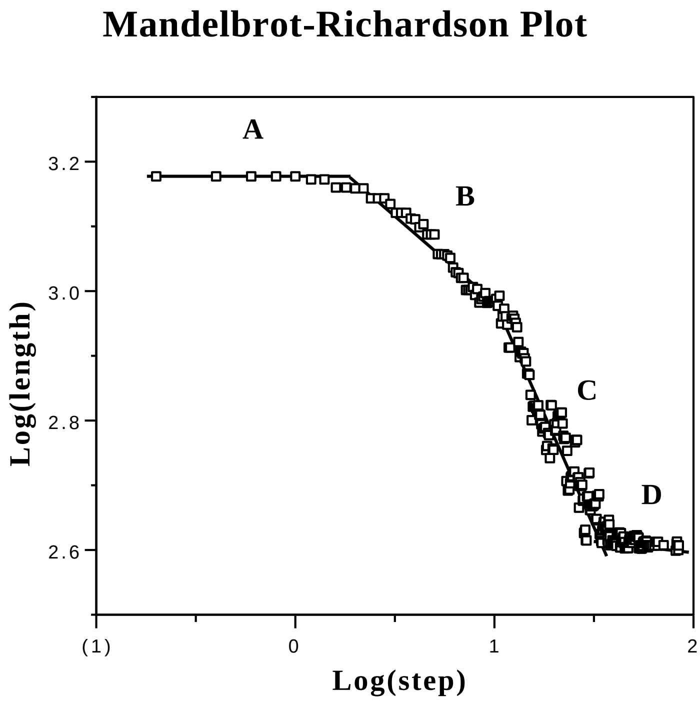

Figure 2.2: Mandelbrot-Richardson plot of a seismic trace. Four sections with different slopes (A-D) are defined. A and D are sampling artefacts. B and C are due to signal and noise components within the trace.

we are not able to recognise any new structure in the curve and again a flat section (A) results. Notice that a linear interpolation between the discrete samples is used. Details about the method implementation may be found in [4]. No generally accepted rules are available in the literature for the choice of the step range to employ in the calculation of the curve length, while indications can be found in [12, 11, 2]. Klinkenberg reports one-half the average distance between adjacent points as a suggested choice for the minimum step size while the maximum step size should be much less than the cross-over distance (see [17]). Such recommendations have been employed in this study although some experimental tuning was also necessary. In the rest of the discussion it is defined as compatible a step range that satisfies the requirements just described in relation with the part of the trace under analysis (i.e. noise or seismic signal).

Even when fractal dimension is carried out using an appropriate step size the Mandelbrot-Richardson plot may still not result in a single linear segment. Curves that give rise to multiple straight line segments are usually referred to as 'multi-fractal'. This phenomenon occurs when a distribution is governed by a limited number of structures, expressing themselves at different scales as in the attempt to measure the fractal dimension of a seismic trace section [11]. The two linear segments in the central part of Figure 2.2 (B and C) are due to the fact that two uncorrelated components are present in a seismic trace, i.e the signal and the noise.

If the 'divider method' is used with a step size which is compatible with the amplitude and frequency characteristics of the noise, the resulting straight line segment on the Mandelbrot-Richardson plot defines the fractal dimension of the noise. The same is true when the step size is compatible with the amplitude and frequency of the signal, with of course the Mandelbrot- Richardson plot defining the fractal dimension of the signal. The relative change in fractal dimension between noise (pre-first break) and noise + signal (post-first break) and its relationship to step size is illustrated in Figure 2.3. In Figure 2.3a when a section of the trace containing only noise is analysed using a step range whose logarithm varies between 0.7-1.5, the slope of the straight line segment is -0.89. When a step size whose logarithm exceeds 1.5 is used the plot is horizontal. Figure 2.3b shows the Mandelbrot-Richardson plot for a section of the trace containing both noise and signal. As in Figure 2.3a, at step sizes whose logarithms are less than 1.5 the straight line segment reflects the noise component within the trace. However, in the presence of signal, at step sizes greater than 1.5 a second straight line is observed. According to Mandelbrot, in the part of the Mandelbrot-Richardson plot for step sizes of between 0.7 and 1.5 the slope of the two lines should be identical in Figure 2.3, because when two fractal sets are unified the calculated fractal dimension should equal that of the higher dimensional component. Clearly this is not the case with the seismic trace and I note that Russ [19] describes practical calculations showing that in such a case the fractal dimension assumes an intermediate value.

2.2.2 Calculation of fractal dimension using the 'Hurst method'

In the 'Hurst method' the fractal dimension is calculated by determining the range of the data within windows of different size. The maximum difference observed in a window of a given size is normalized by dividing by the standard deviation of the data. If the data follow a fractal model we have:

$$\frac{R}{S} \propto F^{H} \tag{2.3}$$

where R is the maximum difference observed in a window, S is the standard deviation, F is a constant and H is called the Hurst exponent. The Hurst exponent is related to the fractal dimension by the equation:

$$D = 2 - H \tag{2.4}$$

and it can be obtained by plotting the normalised maximum difference against the window size in log-log space (Russ, 1994).

Again, as when using the 'divider method' over a range of step sizes, a straight line on the Hurst plot is to be expected only over a limited range of window sizes.

Figure 2.4 shows the Hurst plot for the same seismic trace used in Figure 2.2. The data define a straight line only at the left-hand side of the figure, i.e. for small window sizes, while for larger windows the

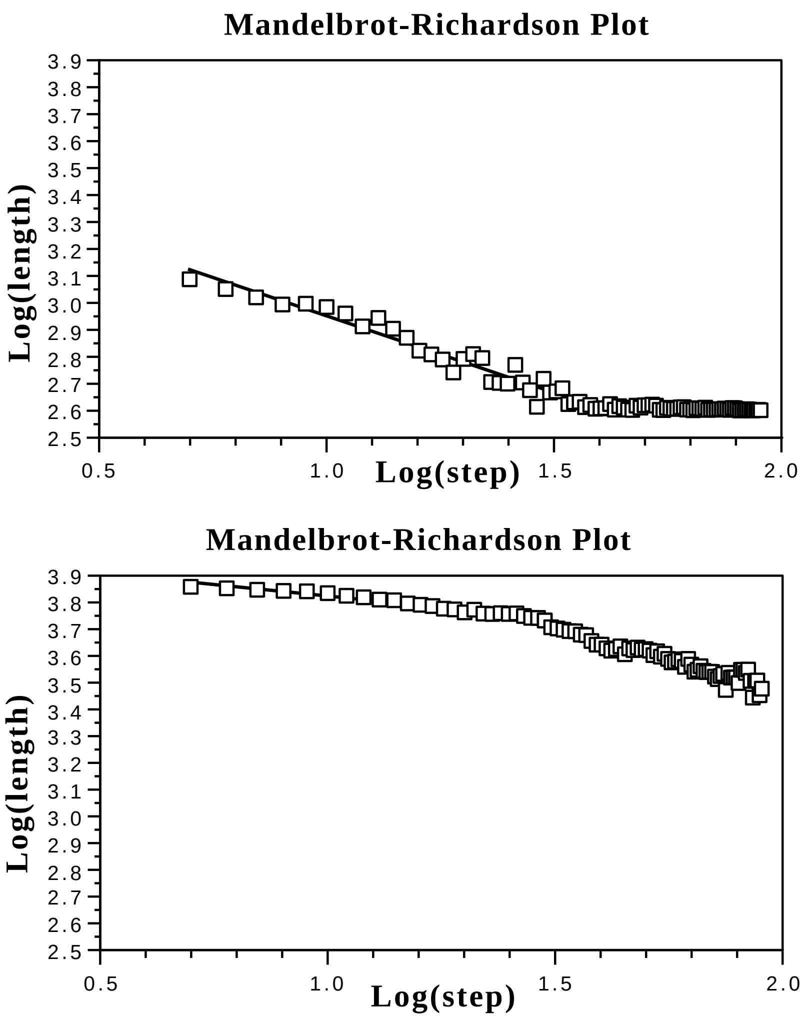

Figure 2.3: Mandelbrot-Richardson plot of a seismic trace containing (a) only noise and (b) signal and noise. Where the log(step) is in the range 0.7-1.5, the 'noisy' section has a higher fractal dimension. Where the log(step) is in the range 1.5-2.0 the situation is reversed.

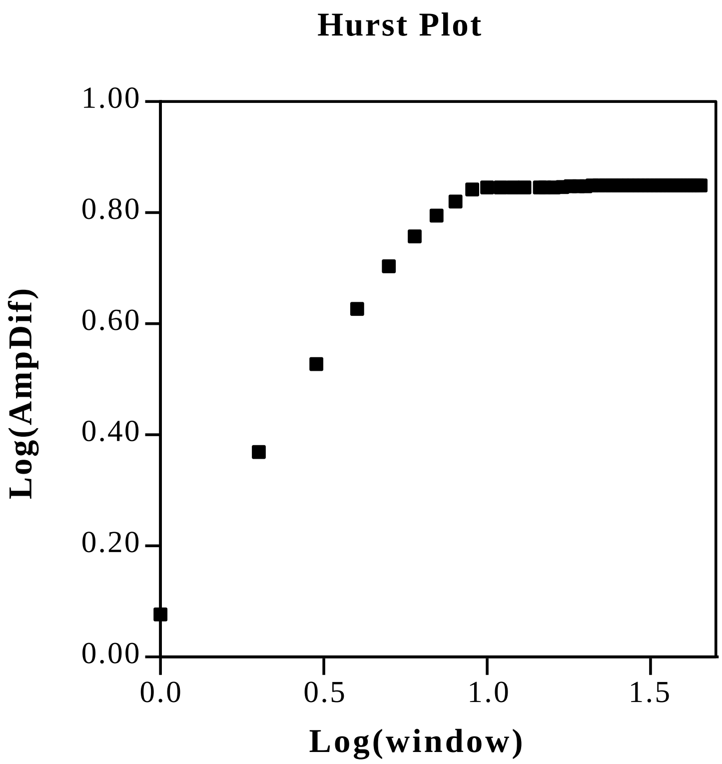

Figure 2.4: Hurst plot of a seismic trace. The sloping segment at the left-hand side of the plot is due to the fractal behaviour of the trace. The flat segment at the right-hand side of the plot is caused by the seismic trace not being a perfect fractal.

normalised difference becomes constant. This is again a consequence of the seismic trace not being a perfect fractal and its representation as a series of samples. Obviously, the greatest difference that can occur within a given window is limited to the maximum and minimum amplitude within the trace. Once the points with the maximum and minimum amplitude are both contained in a window of a certain width, any larger window will not be able to find greater differences in value. Thus, all the points in the 'Hurst plot' obtained for window larger than this size will share the same value. The practical result of this observation is that for a seismic trace whose amplitude will have been re-scaled to lie within arbitrary limits, only a limited window size yields useful data. For instance, in Figure 2.4 only 9 points are significant. In some circumstances, the calculation of the fractal dimension with so few points may not be reliable.

The Hurst method has the advantage that it requires much less computation than the 'divider method', and can be implemented around 1-2 orders of magnitude faster. As will be shown below, it works well in high or medium signal-to-noise traces, but its performance is inferior to that of the 'divider method' on noisy traces. Since the main aim of the fractal-based picking technique presented in this paper is to be robust in presence of noise, even at the cost of time, the 'divider method' is preferred.

2.3 First Break Detection Algorithm

The basis of our first-arrival detection algorithm is that a change in fractal dimension is expected when the trace ceases to consist of just noise and begins to consist of both signal and noise.

Figure 2.5 illustrates how the algorithm works. First the approximate region of the trace containing the first break is selected manually. A window is then moved across this region and the fractal dimension of that part of the trace within the window is calculated. When the window is entirely before the first- arrival time it only contains noise - window A in Figure 2.5. When the window includes the first-break some of the trace consists of just noise and some of signal plus noise - window B in Figure 2.5. When the window passes the first arrival it

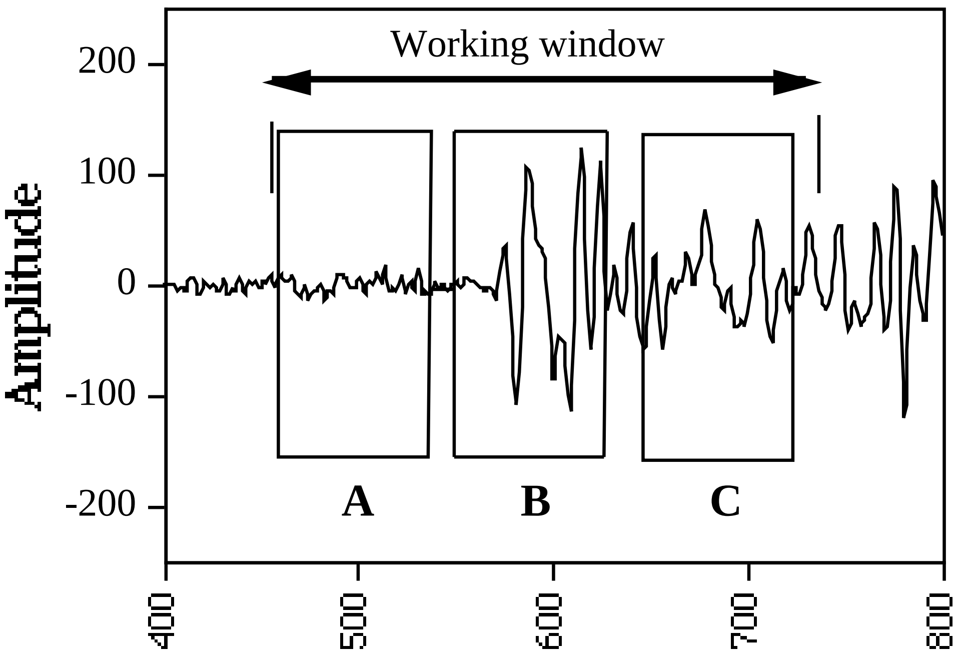

Figure 2.5: Schematic illustration of how the variation in fractal dimension along the seismic trace is calculated. The working window is manually selected to contain the first break. A smaller window is then moved progressively along the trace and the variation in dimension plotted as a function of the maximum time within the window.

is completed filled by that part of the trace containing both signal and noise - window C in Figure 2.5. The value of the fractal dimension is calculated for each window and plotted at the location of the maximum time of the window. Figure 2.6 illustrates the change in fractal dimension of the trace within the window using two different step ranges (one compatible with the noise and one compatible with the signal). The seismic trace is also shown for comparison (Figure 2.6a). With both ranges in step size, before the window reaches the first arrival the fractal dimension is almost constant. When the window reaches and passes the first arrival time the fractal dimension changes quite rapidly before again assuming a near constant value. The absolute value of the fractal dimension measured on different traces may vary, depending on the signal-to-noise ratio, on the amplification of the signal and on the sampling frequency but the overall shape of the fractal-dimension curve is the same. It is interesting that depending on the range of the step size there may be either an increase or decrease in fractal dimension associated with the presence of signal. This depends whether the range in steps sizes is compatible with the noise or the signal. However, for the purposes of detecting the first arrival the nature of the change is unimportant.

The plots in Figure 2.6 showing the variation in fractal dimension along the trace are characterised by three distinct segments: a flat segment (A) indicating the fractal dimension of the noise, an inclined segment (B) associated with the change in fractal dimension, and a second flat segment (C) associated with areas where the signal is dominating the trace. The intersection between the first flat segment (A) and the steep segment (B) occurs a few steps after the first arrival time. This is due to the fact that the algorithm needs a few points to detect the presence of the signal. The delay between the intersection of the two segments and the first arrival time rarely exceeds a signal wave-length. This means that to detect the first arrival we can determine the intersection of these two segments (A and B), then run backwards along the trace until a local amplitude extreme is found. If required, the delay between the first amplitude extreme and the first break can be determined using traces with a high signal- to-noise ratio, and subtracted from the arrival time determined by the algorithm. More sophisticated methods, taking into account the correlation with adjacent traces may

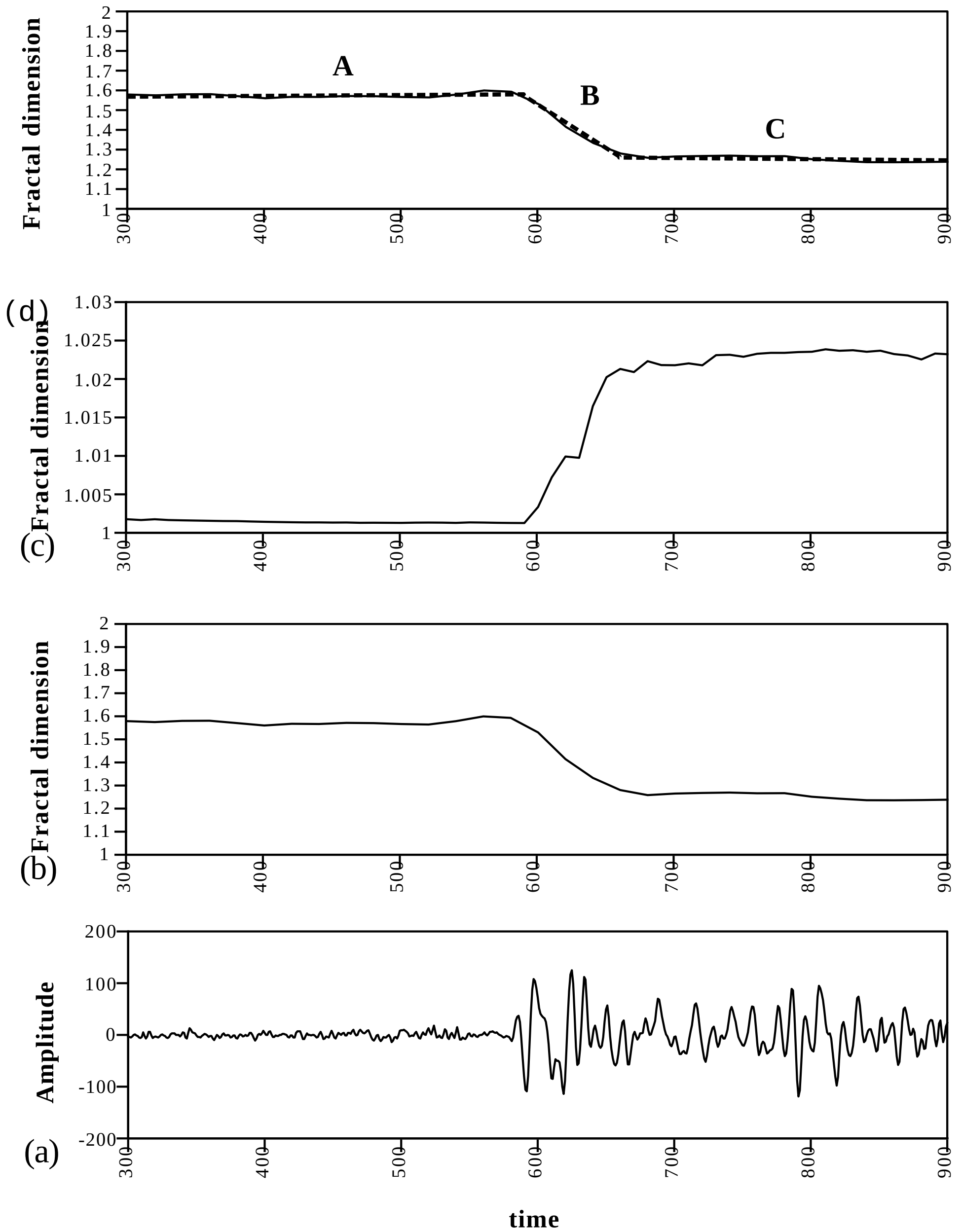

Figure 2.6: (a) Seismic trace. (b) Fractal dimension of the sections to the left of a cursor moving along a seismic trace, in the case the investigation is carried on in a range compatible with the noise amplitude and frequency. (c) Same as in (b), but now the investigation is carried on in a range compatible with the signal amplitude and frequency. Fractal dimension as in (b) approximated by 3 straight-line segments.

also be implemented.

2.4 Experimental Results

The effectiveness of the 'divider method' and the 'Hurst method' based algorithms were compared with each other, and with other algorithms designed to detect first breaks described in the literature. To assess their relative merits in the presence of noise three different field data sets were used:

1. a data set, with a very high signal-to-noise ratio,

2. a data set with a medium signal-to-noise ratio,

3. a data set with a very low signal-to-noise ratio,

The first data set has been collected during a seismic reflection survey across a granitoid-greenstone terrain in Western Australia (Nevoria seismic experiment, see [6]). The second data set comes from the WISE experiment (Western Isles Seismic Experiment), an offshore seismic refraction experiment in western Scotland. The last data set is part of a crustal scale refraction experiment across the southern part of the Yilgarn Craton in Western Australia (see [1]). The fractal-based algorithm was able to pick the correct first arrival on the high and medium signal-to-noise data sets using either the 'divider method' or the 'Hurst method'. On the low signal-to-noise data set the algorithm could pick most of the traces employing the 'divider method', failing only on traces even an human operator would be unable to discriminate between noise and signal on. However, the 'Hurst method' proved not to be effective on this data set, due to instabilities caused by the few points used to calculate the fractal dimension. In these tests the 'divider method' was used for a range of step sizes and although the nature of the change in fractal dimension varied the algorithm was still successful.

The performance of the 'divider method' algorithm was compared on the medium signal-to-noise data set with those of five published picking algorithms [7, 18, 9, 5, 16]. Such algorithms were developed in order to be applicable to field data with no particular limitations and they are representative of different kinds of picking methods available in the literature. Coppens' [5] method is based on the detection of a sudden increase in energy on a trace, Gelchinsky's [9] and Peraldi's [16] methods are based on different kinds of correlation with adjacent traces, while Ervin's [7] and Ramananantoandro's [18] algorithms look for the first arrivals by convoluting the seismic traces with different operators. Of these, the most effective algorithms proved to be Gelchinsky's, Coppens', and Peraldi's, whose results, together with the ones from the 'divider-method' algorithm are compared in Figure 2.7. Only the fractal-based algorithm is able to pick the correct first arrival on all the traces. Note that, as described above, the fractal-based method detects the first amplitude extreme after the first arrival.

Progressively larger amounts of random noise were added to the high and the medium signal-to-noise ratio data sets in order to estimate the maximum amount of noise the fractal-based algorithm could tolerate. The algorithm was still able to detect the correct pick after noise, whose average amplitude was 80% of the average amplitude of the signal, was added. However, for the algorithm to be successful in this case a step range compatible with the signal structure is required. This is particularly important in the presence of large amounts of noise because the relative change in fractal dimension associated with the onset of the signal will be relatively small when using step ranges compatible with the noise.

Notice that the divider method gives a measure of the roughness of the section of the trace under analysis, that depends on the amplitude, frequency, and phase of noise and signal all together and not on any single component alone. The algorithm then detects the change in the overall shape of the curve, simulating the way a human brain discriminates the presence of signal in the seismic trace. Such discrimination is effective also in presence of high level of noise (see results shown in Figure 2.8) and does not depend on single characteristics of the signal, such as frequency or amplitude. Accordingly, unlike most common picking algorithms, no preprocessing or filtering of the data is necessary.

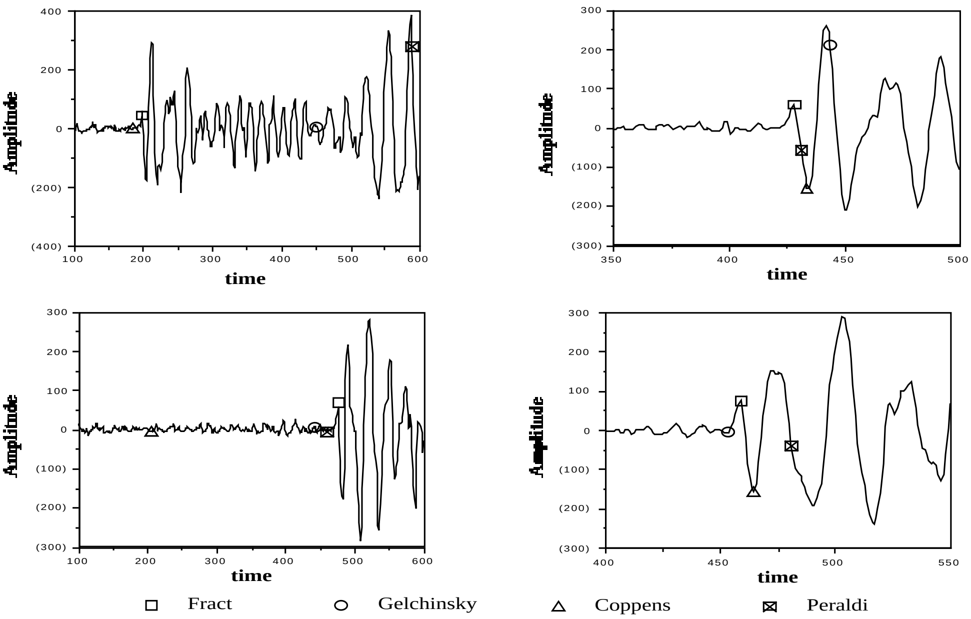

Figure 2.7: Comparison between the fractal-based algorithm and three algorithms from the literature. The fractal-based algorithm is able to pick the correct arrival time in all the traces while the other algorithms may occasionally show relevant errors.

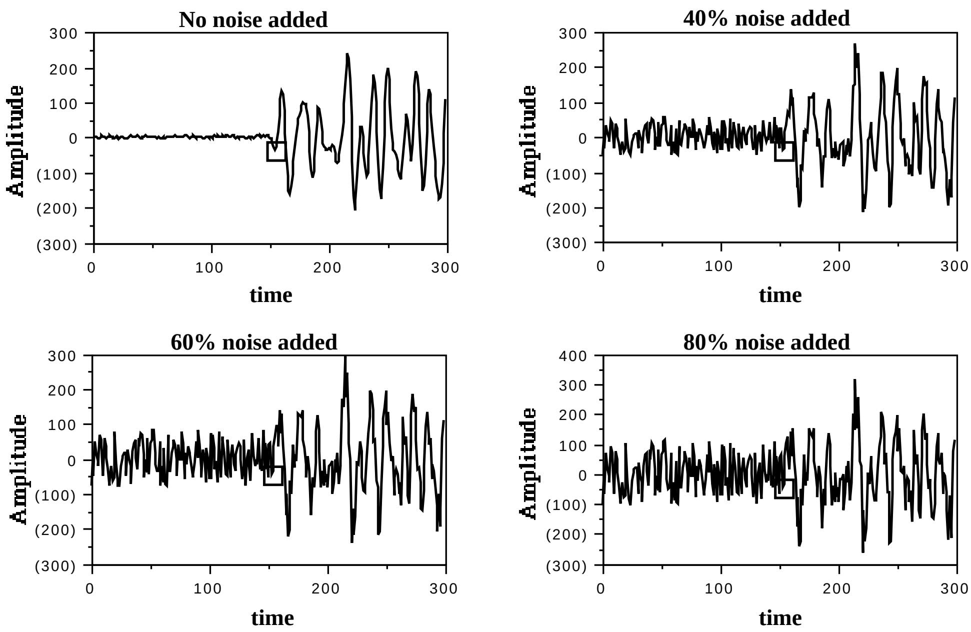

Figure 2.8: Progressively increasing amount of noise added to a high signal-to- noise seismic trace to assess the maximum level of noise the code can tolerate. The fractal-based algorithm can still detect the correct pick after an amount of noise up to 80% of the average signal amplitude is added.

2.5 Discussion

The fractal-based picking algorithm requires a relatively large amount of calculation compared to other first-arrival detection algorithms (approximately one order of magnitude larger that Coppens method). The fractal dimension calculation requires the measurement of the length of the seismic trace within the window for different step lengths and then regression of the points so obtained. This must be performed for a window located at each point of the trace. Also, significant effort is required to define the three segments that best fit the fractal dimension curve. The implementation of the fractal-based algorithm is quite straightforward, but both the accuracy of the result and the speed of the code depend critically on the tuning of a different number of parameters. In particular the influence of such a tuning on the speed may be crucial, allowing performance improvements up to 1-2 orders of magnitude.

Second arrivals may alter the shape of the plot in Figure 2.6b and 2.6c. In such circumstance, the flat segment corresponding to the signal fractal dimension may be substituted by a curve of different shape depending on the characteristic of the second arrivals. However, the contact between the first and second segment in Figure 2.6b and 2.6c will be unchanged and consequently only minor modifications to the algorithm will be required in order to detect the first arrival. If possible, such problem could be eliminated by selecting an appropriate window and letting the algorithm run only on the section of the trace where the first arrival is known to be. In this way wasted time spent investigating useless areas would also be avoided.

In terms of speed, the most important parameter is the step size of the window along the trace. In the previous discussion it was assumed that the calculation of the fractal dimension took place at each point along the trace. As described in the section First Break Detection Algorithm, the real arrival time is determined running backward from the intersection of the two segments until an amplitude local extreme is found. Accordingly, carrying out the calculation every 5-10 points, and so doing reducing the amount of calculation of 5-10 times, does not affect the result. Obviously the maximum step allowed depends of the frequency of the signal and must not exceed the signal wavelength.

An even faster calculation may be carried out with a very long window step, just to detect the area where the first arrival is located, and performing a more accurate search with a shorter step in that area. The effectiveness of such an 'accelerating' process depends strongly on the signal-to-noise ratio: the simpler the trace the faster the algorithm can be run. In our experiments the parameters have been tuned on the most complex traces, and then this configuration has been used on all the traces. Another solution is to tune the parameters for fast operation using a medium complexity trace and to use a slower but more accurate configuration for the hardest traces whose first arrivals were not detected.

2.6 Conclusions

In this chapter it has been shown that the difference in fractal dimension between the part of a seismic trace containing only noise and a section containing noise plus seismic signal can be used to detect a seismic first arrival.

Analysis of the variation in fractal dimension along numerous traces highlights a consistent pattern which may be approximated by three segments. A segment associated with noise, a segment associated with the transition from noise to signal and noise, and a segment due to signal and noise. The proposed picking method relies on the fact that the contact between the first and the second segment falls just few steps after the first arrival time. Different techniques may then be used to detect the correct pick-time, the most favoured being running backward along the trace till a local amplitude minimum is found. The algorithm has been tested on different real data sets and works well even when signal-to-noise ratio is low.

Bibliography

[1] B. A. Bolt, H. A. Doyle, and D. J. Sutton. Seismic observation from the 1956 atomic explosions in australia. *Geophysical Journal of the Royal Astronomical Society*, 1:135–145, 1958.

[2] S. Brown. A note on the description of surface roughness using fractal dimension. *Geophysical Research Letters*, 14:1095–1098, 1987.

[3] J. R. Carr and W. B. Benzer. On the practice of estimating fractal dimension. *Mathematical Geology*, 23:945–958, 1991.

[4] M. W. Clark. Three techniques for implementing digital fractal analysis of particle shapes. *Powder Technology*, 46:45–52, 1986.

[5] F. Coppens. First arrival picking on common-offset trace collections for automatic estimation of static corrections. *Geophysical Prospecting*, 33:1212–1231, 1985.

[6] M. C. Dentith, M. C. Jones, and A. Trench. Exploration for gold-bearing iron formation in the burbidge area of the southern cross greenstone belt, w.a. *Exploration Geophysics*, 23:111–116, 1992.

[7] C. P. Ervin, L. D. McGinnis, R. M. Otis, and M. L. Hall. Automated analysis of marine refraction data: A computer algorithm. *Geophysics*, 48:582–589, 1983.

[8] J. Feder. *Fractals*. Plenum, 1988.

[9] B. Gelchinsky and V. Shtivelman. Automatic picking of first arrivals and parameterization of traveltime curves. *Geophysical Prospecting*, 31:915–928, 1983.

[10] J. Hayward, J. D. Orford, and W. B. Whalley. Three implementations of fractal analysis of particle outlines. *Computers and Geoscience*, 15:199–207, 1989.

[11] B. H. Kaye. *A random walk through fractal dimension.* VCH publishers, 1989.

[12] B. Klinkenberg. A review of methods used to determine the fractal dimension of linear features. *Mathematical Geology*, 26:23–46, 1994.

[13] B. Mandelbrot. How long is the coast of britain? statistical self-similarity and fractional dimension. *Science*, 156:636–638, 1967.

[14] B. B. Mandelbrot. *Fractals: form, chance and dimension.* Freeman, 1977.

[15] B. B. Mandelbrot. *The fractal geometry of nature.* Freeman, 1983.

[16] R. Peraldi and A. Clement. Digital processing of refraction data, study of first arrival. *Geophysical Prospecting*, 20:529–548, 1972.

[17] W. Power and T. Tullis. Euclidean and fractal models for the description of rock surface roughness. *Journal of Geophysical Research*, 96:415–421, 1991.

[18] R. Ramananantoandro and N. Bernitsas. A computer algorithm for automatic picking of refraction first-arrival time. *Geoexploration*, 24:147–151, 1987.

[19] J. C. Russ. *Fractal surfaces.* Plenum Press, 1994.

[20] C. H. Scholz and B. B. Mandelbrot. *Fractals in geophysics.* Birkhauser Verlag, 1989.

[21] D. Turcotte. *Fractals and chaos in geology and geophysics.* Cambridge University Press, 1992.