Chapter 1

Introduction

1.1 Scope of the work

The initial aim of this project was to obtain further insights into the problems related to the inversion of seismic refraction data. This was motivated by the growing interest in the possibility of employing refraction surveys in the investigation of regolith profiles in Western Australia.

The mathematical tools traditionally used in this kind of inversion were directly inherited by the first experiments in global seismic tomography, that in turn were inherited by medical tomography (C.A.T. scan), i.e., steepest descent method, conjugate method, Marquardt-Levemberg method etc... [13, 11]. This family of techniques, referred to as local optimisers in the rest of the document, have a number of inherent limitations that can strongly affect their effectiveness in seismic applications. In particular these include:

- they often need linear approximation of the problem to be solved, that results in inaccuracies in the process;
- they require a starting model;
- they often need derivative evaluations, not always available in real world complex functions;
- they can easily get trapped in local minima;

- a single solution is obtained as a result of the inversion process.

Among these, the need of detailed 'a priori' information, to avoid being trapped in local minima very far from the global one sought is the most demanding, because rarely the amount of 'a priori' information required to correctly select a suitable starting model is available in geophysical inversion problems.

To overcome these drawbacks new search techniques, often referred to as 'global search' methods, were proposed during the 70s and the early 80s and applied to a large variety of non-geophysical inverse problems. Some of these techniques were based on some kind of gridded search [10, 8], while others were based on guided random search [9, 19, 15, 20], but they share a common theme, i.e., to allow the algorithm to span an area of the search domain as large as possible and to concentrate the successive search on the most promising areas currently discovered.

Among these, three methods became increasingly popular due to their success in broadly different global optimisation applications. These techniques, Simulated Annealing [12], Genetic Algorithms [7], and Neural Networks [14], have the common idea of simulating Nature. The observation that Nature is often able to solve very difficult problems without knowledge of all the details of their global process in the source of this common idea.

Also, Genetic Algorithms and Simulated Annealing shared a major characteristic: to allow the process to keep on sampling new areas in the solution space even when a good solution has already been found. This last point is crucial in order to avoid the search getting trapped in local minima.

Despite their completely different origin, Genetic Algorithms and Simulated Annealing were following a kind of parallel development: they were applied to increasingly different and complex problems, both theoretical and real world, and were often tested against one another.

In order to decide whether to concentrate this research on the use of Genetic Algorithms or Simulated Annealing a number of factors had to be taken into account. Simulated Annealing possesses a theoretical proof of its convergence. Currently Genetic Algorithms still lack this proof. However, most of the direct comparisons available in the literature showed that Simulated Annealing required a too large computational effort to approach most of large real world optimisation problems. Such computation effort, despite still very heavy, seemed more accessible with Genetic Algorithms.

Before the beginning of my project only very few attempts to apply Genetic Algorithms to the inversion of geophysical data had been published [16, 17, 18].

I though that further analysis of the potential of Genetic Algorithms in geophysical problems was worthwhile because of the advantages that they seemed to offer over local search techniques:

- they perform a global search;
- they need a minimum amount of 'a priori' information, usually limited to the problem parameterisation;
- they do not need derivative calculation;
- they are based only on direct space sampling, and accordingly no linearisation of the problem is required;
- they can produce multiple solutions in a single inversion run.

I first applied Genetic Algorithms to a seismic refraction tomography problem. The inversion of seismic refraction data is difficult mainly because of its high-non linearity and its large dimensionality. Common applications of Genetic Algorithms are performed on far smaller dimensional problems. The fact that this represented a difficult test for Genetic Algorithms was confirmed by discussions I had with overseas researchers in the field of optimisation.

A crucial step in the research has been the inclusion of a 'pseudo subspace search' in the Genetic Algorithm process. This has been motivated by Williamson [21] who successfully applied a similar technique to local optimisation. The inclusion of this method in the Genetic Algorithm global search, which allows the dimensionality and complexity of the problem to be progressively increased during the inversion, has been fundamental in the success of all the experiments I performed and it is an essential part of the Genetic Algorithm described in Chapter 4.

The good results obtained with many synthetic models, a physical model and real seismic tomography problems (presented in Chapter 5), justified the extension of the method to other geophysical problems. Testing the Genetic Algorithms on the inversion of magnetic and gravity data is described in

Chapter 6. Here the ability of Genetic Algorithms to simultaneously generate a large number of different solutions during the convergence process allowed the description of the ambiguity inherent in potential field problems. The collection of an equivalent number of different solutions with traditional local optimisation methods would have required a large number of individual runs and consequently a much larger computational effort. This shows one of the computational advantages of Genetic Algorithms. Promising results have been obtained both with synthetic and real potential field data.

During the course of my studies, research in Genetic Algorithms developed fast. Also, a considerable effort into the application of Genetic Algorithms to geophysics has been produced and a number of papers has been recently published. However, it is currently difficult to clearly establish their full potential as well as their inherent limitations. Theoretical studies to understand which kind of problems are better suited to be adressed by Genetic Algorithms have been published but they are not conclusive and currently applications seem to proceed one step ahead. Consequently, it is also hard to evaluate the possible future impact of Genetic Algorithms on standard geophysical exploration techniques.

A number of steps need to be taken in order to evaluate this potential. My research attempeted at covering two of these steps. First, it is shown that Genetic Algorithms are an effective tool in dealing with the theoretical aspects of two completely different geophysical problems, seismic refraction and potential field inverse problems. This has been achieved by analysing the Genetic Algorithms performances on a set of synthetic data sets. Secondly, Genetic Algorithms have been successfully applied to the inversion of different real data sets. They showed that they should be considered as a possible fast tool for a preliminary analysis of field data.

The experience obtained in these experiments has also outlined some of the problems that should be adressed in order to extend the application of Genetic Algorithms to more complex geophysical problems. These are listed in the conclusions at the end of the report.

1.2 Thesis organisation

The following brief description of different chapters included in this document gives an overview of the thesis content and shows its logical development.

Prior to attempting the actual inversion problem two algorithms to detect and to calculate seismic first arrivals have been developed as part of the seismic problem. The picking algorithm here presented is original and it detects the first arrivals by analysing the change in fractal dimension along seismic traces. The work has been recently accepted for publication in GEOPHYSICS [2] and the paper is reproduced, with minor variations, in Chapter 2.

The ray-tracing algorithm is a modified version of an already published algorithm [1]. The modification approximates linearly varying slowness between nodes in the domain. A detailed description of the algorithm is reported in Chapter 3, while the FORTRAN77 code is presented in Appendix A.

In Chapter 4 the ideas behind the different Genetic Algorithms employed in this study are discussed. The details about the pseudo subspace method, presented at the International Conference on Evolutionary Computing ICEC95 [3], are also described. The FORTRAN77 code for the two Genetic Algorithms programs used in the seismic and potential field applications are reported in Appendix B.

Chapter 5 contains the application of Genetic Algorithms to seismic refraction tomography. The description of the synthetic and the real data inversions are taken from a paper submitted to GEOPHYSICS [5], while the physical model experiment has been already published in EXPLORATION GEOPHYSICS [6].

Chapter 6 contains the Genetic Algorithms application to the inversion of gravity and magnetic data. Here the inversion of both synthetic and real data sets is discussed. This work has been submitted to GEOPHYSICAL PROSPECTING [4] and it is currently under review.

Chapter 7 presents some observations on the role of noise in inverse problems. It is shown that the effects in seismic refraction tomography due to inaccuracies in the forward model calculations is such to mislead the inversion procedure towards a wrong solution. The reasons for this phenomenon are discribed and a method to detect the areas of the solution more sensitive to errors is proposed. The use of gravity data in order to better constrain the seismic inversion is also proposed and tested on different synthetic tests. The content of this chapter has been recently submitted to GEOPHYSICAL JOURNAL INTERNATIONAL.

Finally, Chapter 8 contains some general conclusions that may be drawn from the overall work together with indications for further development of the research.

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