UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

Joint Orthogonal Coding and Pulse Compression for Low-Power Polarimetric Radar

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE IN METEOROLOGY

By

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Norman, Oklahoma
2011

Joint Orthogonal Coding and Pulse Compression for Low-Power Polarimetric Radar

A THESIS APPROVED FOR THE
SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

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Dedication

This thesis is dedicated to my parents and my wonderful wife. Thank you for investing in me by sacrificing so much, and thank you Myka for your patience over the last 6 years with my techie-stuff.

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Abstract

Orthogonal coding foo bla awesome, but even better with pulse compression, so yeah.

Chapter 1

Introduction

? and **?** refer to this problem as the "data assimilation" problem. But I can write this sentence a different way: Consequently, this problem is referred to as the "data assimilation" problem (**??**). I will let the text run on here a bit so that a big reference list will be generated.

Formally, let c be a control vector of size m and S denote the feasible region for the control vector. For any c in S, let $J(c)$ denote the weighted sum of the squared difference between the observation and the solution of the model corresponding to the control vector c. Except in trivial cases the explicit form of J as a function of c is not known. It is to be emphasized that there are other possible choices for the J function. One may be interested only in the state of the model at a given time instant, say $t = \Delta$. Whatever be the nature and type of the J function, mathematically, the data assimilation problem can be stated as follows : find a c^* in S such that $J(c^*)$ is a minimum, that is, we are lead to an optimization problem under the dynamical constraints of the model equations. Since J is a "smooth" function, one method for finding c^* is to use one of the many variants of the classical gradient method. This is however, more easily said than done. The difficulty primarily stems from the fact that J is not known explicitly. A now popular method for finding the gradient of J is called the "adjoint" method (**??**). A summary of data assimilation using the adjoint method is shown in Fig. **??** and described below:

Considerable success has been reported in the literature in the use of adjoint method for finding c^* (**???**). The success of this combination is largely dependent on the properties of the J function. This approach can succeed only if J is unimodal in

S. It turns out that the modality of J critically depends on the model dynamics. It is now known that the nonlinearity in the model dynamics induces multimodality in the J function (**??**).

There are at least two factors affecting the rate of convergence of the iterates leading to the optimum value of the J function. First, is the number and distribution of the observations. There is a minimum number of observations required from an algorithmic viewpoint, but satisfaction of this requirement is insufficient to guarantee a solution. The distribution of these data (in space and time), in concert wtih the dynamics, dictates the existence of a solution. Second, is the shape of the J function. Judicious choice of scaling can remove eccentricities in the J-field. It is thus imperative to understand the role of these two factors affecting the iterates.

The effect of the number and distribution of observations on the quality of the iterates are often examined using controlled experiments which have come to be known as the "twin" experiments. In this, a point in the feasible region for the control vector is first chosen and then the model solution is calculated for this value of the control vector . Then observations (including known error) are generated from the model solution by adding noise with known characteristics. By computing the optimal estimate of the control vector for different sets of observations, we can develop a better understanding of the dependence of the optimal estimate on the number, distribution and accuracy of observations.

As for the shape of the J function, since it is not known explicitly, we must be contented with the analysis of the properties of J around the local minima. This is often done by approximating J around the optimum c^* using a quadratic form such as

$$J(c) = \frac{1}{2}c^t Hc + p^t c + q, \tag{1.1}$$

where H is the Hessian matrix which is a symmetric matrix of the second derivatives of J with respect to c,

$$p = (p_1, p_2, p_3, p_4, ..., p_n)^t \tag{1.2}$$

is a vector and q is a constant. By analyzing the eigenvalues of H, we can draw inferences on the shape of J in the vicinity of c^* (**?**). For example, if one of the eigenvalues of H is very small, then the contours or the level curves of J for the valley around c^* are elongated ellipses. This would imply that the iterative process of locating the minimum would converge slowly and with difficulty.

In this dissertation, one aim is to apply the adjoint method to the mixed layer model (**??**). This model is used to predict the return flow of the warm, humid air from the Gulf of Mexico into the coastal plains during the winter months. The mixed layer model has a small number of unknown variables/parameters. Athough small, the model is nonlinear and thus presents difficulties in dynamical optimization. With the experience gained, we wanted to analyze the computational aspects of data assimilation. This brought us to the shallow water equations (**?**), which has a larger number of variables in the discrete model. We are interested in solving some of the computational aspects of this model that are relevant to data assimilation. Since the solution of the forward model and the adjoint take a good fraction of the efforts, we turned our attention to parallel methods for solving this class of equations.

The shallow water model is discretized first using the Euler scheme. But due to its instability, we also examined the solution using a stable leapfrog scheme. Both types of discretization resulted in a block bi-diagonal system of equations for the forward model and the adjoint model. We are interested in examining the comparative analysis of four vector/parallel algorithms in solving this system of equations. These four vector/parallel algorithms belong to a class of direct parallel methods. The first algorithm is also known as the "divide and conquer" method (**?**). The second algorithm is a variation of the divide and conquer method (**?????**). The third algorithm is known as the partition algorithm (?). The fourth algorithm is the cyclic reduction method (?). A comparison of these four vector/parallel algorithms is done on the CrayJ90 in scalar mode and using 1,2,4 and 8 vector processors.

This dissertation is organized as follows. A description of the use of encapsulated postscript files is presented in Chapter ??. One way to present bargraphs is shown in model equations are described in Section ??. Some example tables are shown in Section ??.

Bibliography