Parallel Implementation of an Inversion Model for Hyperspectral Remote Sensing

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Abstract

This paper describes the implementation of a semi-analytical inversion model within a parallel processing framework. The greater processing speed obtained with this parallel implementation is demonstrated. A reduction of 97% in the execution time is achieved. This approach enables real time processing capabilities and more complex analysis to simultaneously classify water properties, bathymetry and benthic composition associated with coral reefs and other shallow costal subsurface environments.

I. INTRODUCTION

Remote sensing is increasingly being employed as a significant component in the evaluation and management of coral ecosystems. Advantages of this technology include both the qualitative benefits derived from a visual overview, and more importantly, the quantitative abilities for systematic assessment and monitoring. Much of the past work on remote sensing of coral reefs has focused on the use of more traditional multispectral sensors, which collect information from a few discrete non-contiguous portions of the electromagnetic spectrum. However, hyperspectral sensors, which collect information from numerous contiguous portions of the spectrum, are emerging as a more complete solution for subsurface shallow aquatic remote sensing. In contrast with multispectral sensors, hyperspectral instruments provide much greater spectral detail, and thus an improved ability to extract multiple layers of information from a spectrally complex environment associated with coral reefs and other shallow costal subsurface environments. By leveraging this spectral advantage, one of the first successful applications to simultaneously classify water properties, bathymetry and benthic composition using hyperspectral remote sensing was previously demonstrated using AVIRIS imagery from Hawaii [1]. At the core of this approach was the application of a semi-analytical inversion model for simultaneously extracting bathymetry and water property parameters.

Hyperspectral imaging analysis as described above demands large input data sets and requires significant CPU time and memory capacity [2]. For the particular inversion model under discussion, there is a very straightforward parallelization in the spatial domain. Nevertheless, the resulting reduction of elapsed computing time will provide an opportunity for assessing real time processing capabilities and more complex analysis. Another approach is to improve efficiency by means of parallel computations inside the inversion model. This latter approach makes it necessary to develop or modify the corresponding optimization methods.

In this paper we discuss the implementation of the semi-analytical inversion model within a parallel processing framework. The greater processing speed obtained with this parallel implementation is demonstrated. This approach provides both the foundation for assessing real-time processing capabilities as well as the computation power necessary for addressing complex optimization and sensitivity questions. This paper is organized as follows. Section II discusses the semi-analytical inversion model. Section III describes the technical details of the implementation. Section IV presents the experimental results. Finally, conclusions and discussion about future work is provided in section V.

II. SEMI-ANALYTICAL INVERSION MODEL

The semi-analytical inversion model employs a non-linear optimization routine to retrieve estimates of bathymetry and water properties from measured surface remote sensing reflectance data. The algorithm is based on quasi-single-scattering theory, and was developed utilizing Hydrolight (Sequoia Scientific Inc.) simulations to populate parameters of the semi-analytical model [3]. The model is summarized here in Table I following the parameter definitions in Table II. The model operates in the spectral domain and is thus independently applied to each pixel in an image. It requires no specific *a priori* knowledge of the study area and provides the following output for every pixel in the image: *P*, the phytoplankton absorption coefficient at 440 nm; *G*, the absorption coefficient for gelbstoff and detritus at 440 nm; *BP*, a variable representing the combined influences from the particle-backscattering coefficient, view-angle, and sea state; *B*, the bottom albedo at 550 nm; and *H*, the water depth. Using a set of initial estimates for *P*, *G*, *BP*, *B* and *H*, the optimization procedure operates to minimize an error function such that the model estimated remote sensing reflectance from 400-800 nm (calculated from equations in Table I) most closely matches the measured surface remote sensing reflectance. The resulting set of parameter values then provide an indication of the bathymetry and water properties at the location of every pixel.

As test data for implementing the model and evaluating performance, we utilize existing synthetic hyperspectral data generated using Hydrolight as well as actual measured hyperspectral data from already acquired AVIRIS imagery of Puerto Rico and Hawaii [4]. Hydrolight is a physically explicit radioactive transfer numerical model that can be used to generate estimated surface reflectance data for a given set of water optical properties and water depth. AVIRIS, which is operated by NASA's Jet Propulsion Laboratory, measures 224 contiguous spectral bands from 370-2500 nm at a spectral resolution of 10 nm.

TABLE 1. INVERSION MODEL EQUATIONS

$a = a_w + [a_0 + a_1 \ln(P)]P + G\exp[-0.015(\lambda - 440)]$
$Y \approx 3.44(1 - 3.17\exp[-2.01 R_{rs}(440)/R_{rs}(490)])$
$b_b = 0.0038(400/\lambda)^Y + BP(400/\lambda)^{4.3}$
$u = b_b/(a + b_b)$
$r_{rs}{}^{dp} \approx (0.084 + 0.17u)u$
$D_u{}^C \approx 1.03(1 + 2.4u)^{0.5}$
$D_u{}^B \approx 1.04(1 + 5.4u)^{0.5}$
$\kappa = a + b_b$
$r_{rs} \approx r_{rs}{}^{dp}\left[1 - \exp\left(-\kappa H\left[D_u{}^C + 1/\cos(\theta_w)\right]\right)\right] + \frac{1}{\pi}\rho B\exp\left(-\kappa H\left[D_u{}^B + 1/\cos(\theta_w)\right]\right)$
$R_{rs} = 0.5 r_{rs}/(1 - 1.5 r_{rs})$

TABLE II. PARAMETER DESCRIPTION AND UNITS.

Parameter	Description
a	Absorption coefficient, total
a_φ	Absorption coefficient of phytoplankton pigments
a_g	Absorption coefficient of gelbstoff and detritus
a_w	Absorption coefficient of pure seawater
A_0, a_1	Empirically derived coefficients
b_b	Backscattering coefficient, total
b_{bp}	Backscattering coefficient of suspended particles
b_{bw}	Backscattering coefficient of pure seawater
B	Bottom reflectance at 550 nm
BP	Combined coefficient for particle-backscattering, view angle and sea state
$D_u{}^B$	Distribution function for scattered photons from the bottom
$D_u{}^C$	Distribution function for scattered photons from the water
G	Absorption coefficient for gelbstoff and detritus at 440 nm
H	Water depth
κ	Attenuation coefficient
λ	Wavelength
ρ	Bottom reflectance (albedo)
P	Phytoplankton absorption coefficient at 440 nm
r_{rs}	Subsurface remote sensing reflectance
$r_{rs}{}^{dp}$	Subsurface remote sensing reflectance for optically deep water
R_{rs}	Surface remote sensing reflectance
θ_w	Subsurface solar zenith angle
u	Ratio of backscattering coefficient to the attenuation coefficient
Y	Spectral power for particle backscattering coefficient

III. IMPLEMENTATION

We have implemented the semi-analytical inversion model using the Message Passing Interface (MPI) [5]. MPI is the de facto standard specification for implementing parallel applications on distributed memory systems. There exist a number of MPI implementations (e.g. MPICH [6] and LAM-MPI [7]). We are using LAM-MPI 7.1.1 in our implementation.

The problem we address here can be thought of as having a simple decomposition into independent parts that can be processed simultaneously, with communication occurring only at the start and the end of the application. The decomposition permits to send one array of pixels to every processor, for its analysis. It is possible because the analysis of pixels is independent of each other. The master-slave scheme [8] is utilized such that the master coordinates all the process and slaves are in charge of pixels processing.

The ConminC++ Library [9] is used for solving the unconstrained nonlinear optimization problem associated to the semi-analytical inversion model.

IV. RESULTS AND ANALYSIS

The Parallel and Distributed Computing Laboratory (***PDCLab***) at the University of Puerto Rico at Mayaguez (http://pdc.ece.uprm.edu) facilitated the use of an IBM 64 dual-processor nodes xSeries Server cluster running under Linux and LAM-MPI/C++.

The accuracy of the results is compared to those obtained with the original IDL (Interactive Data Language) implementation. Figure 1 illustrates the difference of the IDL and the MPI/C++ implementations for the objective function values at pixels. Notice that the optimization strategies used in IDL and ConminC++ yield similar results. Pixel by pixel only eight of 2,500 pixel produces different results. Figure 2 shows a comparison of water depth error values obtained with IDL and MPI/C++. Actual data is represented by the diagonal in the graph. Notice that for values beyond 8 meters it appears that the IDL code overestimates water depth values. This is a significant result that needs more analysis. This overestimation may be associated to the optimization routine used in IDL.

To examine the performance of the parallelization, we first evaluate execution time and then we demonstrate the scaling of the speedup (ratio of single code execution time over parallel code execution time). Figure 3 shows the dramatic execution time reduction obtained as we increase the number of processors. For 88 processors, for example, we can obtain the minimum time 26,4 seconds, a 2.51% of serial time. Figure 4 illustrates the speedup obtained as we increase the number of processors. Notice that even a superlinear speedup is obtained between 8 and 92 processors indicating maximum efficiency of cache utilization. For the specific machine and problem size of these experiments it is not more cost effective to use beyond 88 processors. To reach more efficiency it is necessary to increase the problem size meaning the size of the images or the number of parameters being analyzed.

V. CONCLUSIONS

The primary objective of this paper has been to demonstrate the efficiency of a parallel implementation of a semi-analytical inversion model for hyperspectral remote sensing analysis. The model has been applied successfully to simultaneously classify water properties, bathymetry and benthic composition associated with coral reefs. The realization of this parallel processing framework will allow investigate alternative optimization schemes for evaluating the inversion model, perform a sensitivity analysis of the inversion model's physical parameters, identify the most significant parameters to adjust for improving model performance, and ultimately develop a more computationally efficient framework for implementing the inversion model. Experimental results show a 97% of efficiency.

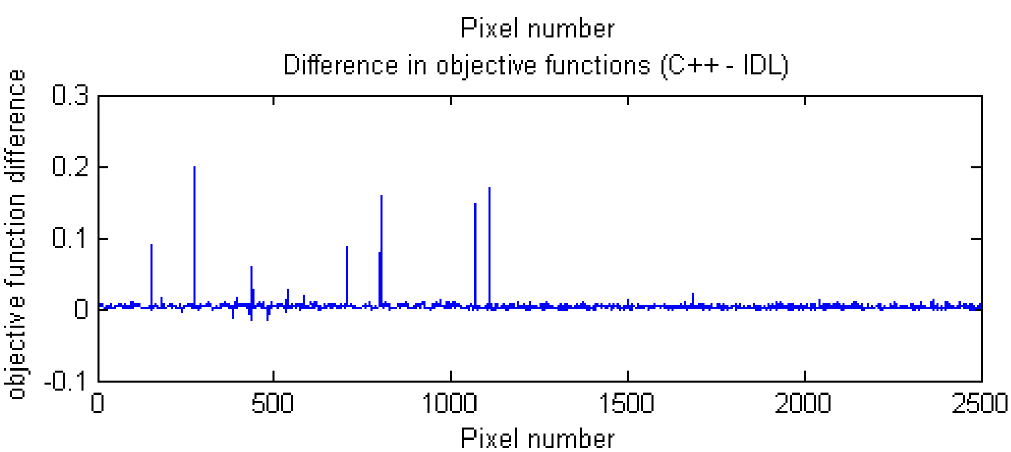

Figure 1. Objective function Difference; IDL vs. MPI

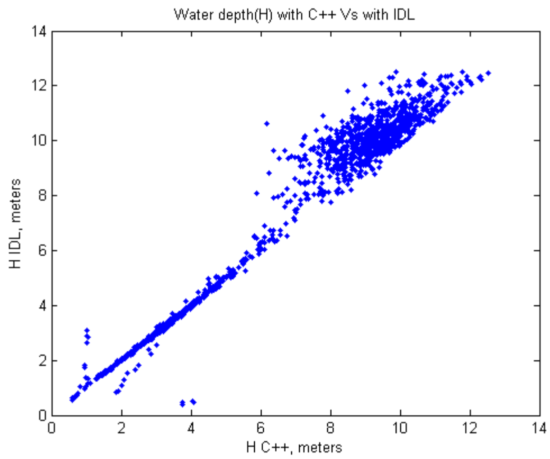

Figure 2. Water Depth Values; IDL vs. MPI

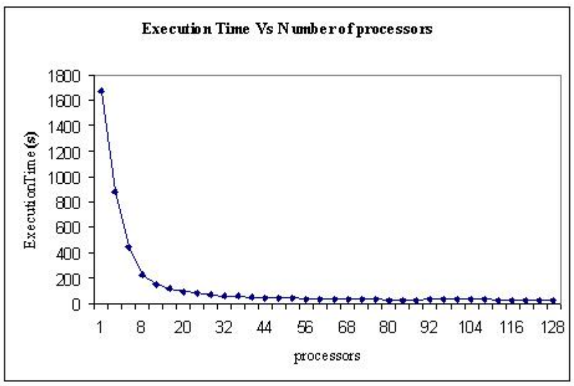

Figure 3. Parallel Execution Times

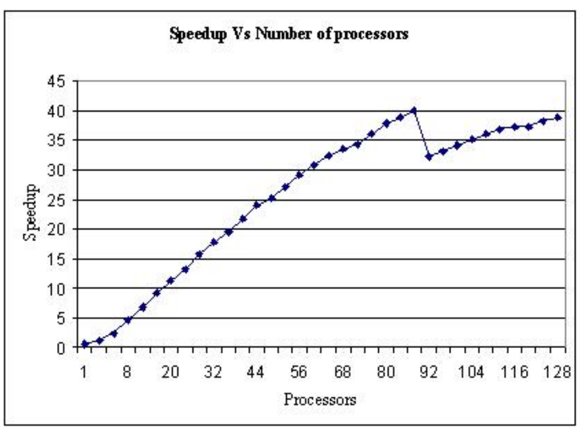

Figure 4. Speedup

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