USING A HIGH THROUGHPUT COMPUTATIONAL GRID FOR THE RETRIEVAL OF AEROSOL PROPERTIES OVER CHINA LAND

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ABSTRACT:

This paper describes the need for and the proposed designing of the high performance quantitative retrieval model to be used on Computational Grid for study of aerosol properties, with particular emphasis on Aerosol Optical Thickness (AOT) determination. A methodology using multi-resource remotely sensed data and adapting available aerosol retrieval model in a Grid environment is demonstrated. The algorithm comprises two complementary parts, collectively used in a distributed application. This paper focused on parallelization method based on a resource management and task partition strategy. A module, called DPPA (Dynamic Partition Points Algorithm for workload estimation), is designed as a portable technology for developing and deploying Grid execution in a generic data parallel paradigm. Experimental results are presented in a realistic application, using data collected by MODIS over China land. Derived result and computing performance of the proposed algorithm is given using the Grid test-bed at the Institute of Remote Sensing Applications of Chinese Academy of Sciences (IRSA, CAS). Combined, the experimental results show that Grid-enabled model allowed on-demand large volume of ground-based data assimilation with parameters, and achieved substantial reductions in computational times. The research gives a thoughtful perspective on the potential of applying high performance computing practices to remote sensing quantitative retrieving problems.

1. INTRODUCTION

Aerosol optical properties are believed to be important for understanding aerosol radiative forcing, and impact on climate change(2001). Due to their high temporal and spatial variability, atmospheric aerosol monitoring is still a difficult task. Satellite remote sensing is an efficient way to monitor aerosol properties on a large scale, because the information provided is both timely and global in coverage. A number of passive satellite instruments have been used to retrieve global distributions of tropospheric aerosol properties. For years, many algorithms have been applied to these satellite datasets to retrieving information useful for studying aerosol over land (Kokhanovsky et al, 2007). The prediction relies on physical dynamic models whose variables must be quantitatively estimated from Earth observing data. However, this procedure needs to apply complex models on selected subsets of large volumes of multi-sensor or multi-temporal data. The increasing complexity of data processing and of retrieving computing has significantly increased computational demands.

In recent years, computational Grid of commodity computers have rapidly become a promising solution, expected to play a major role in high performance computing systems for remote sensing missions (Foster et al, 2001). The new processing power offered by Grid from idle CPUs can be employed to tackle issues stated above. High Throughput Computing (HTC) Grid that can get the considerable amount of works done during task time benefits from distributed, heterogeneous and dynamic resources (Basney et al, 1997). Although the Grid technology seems to offer the potential for enhanced remote sensing retrieval, the scope of this potential remains nearly unexplored in this field of research. Only a few research efforts devoted to the design of Grid-enabled implementations for remote sensing retrieval exist (Chalermwat, 1999;Hawick et al, 1997; Plaza, 2006; Teo et al, 2003;Yang, 2001) And most of them address remotely sensed image processing, but few published for retrieval model.

This paper is concerned with high performance retrieving algorithms based on genetic Grid platform, with particular emphasis on Aerosol Optical Thickness (AOT) retrieval. We propose this new high performance aerosol retrieval algorithm that is used for Moderate Resolution Imaging Spectroradiometer (MODIS) from Earth Observing System (EOS) satellite data. A methodology using multi-resource remotely sensed data and available aerosol retrieval algorithms in an operational scheme is demonstrated. The algorithm comprises two complementary parts, collectively used in a distributed application. The first part is the modified multi-angle AOT retrieval algorithm described in our previous research publications (Tang et al, 2005), which is used for retrieval over land for a given region. This is a more general

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technique compared to DDV method that is based on the NASA near IR-visible surface albedo correlation approach and therefore restrictedly depends on the surface type (dense dark vegetation, or heterogeneous land) (Kaufman et al, 1997). The ground station data are routinely coming from more than 16 nationwide locations by the AERosol Robotic NETwork (AERONET) of ground-based sun- and sky-scanning radiometers (Smirnov et al, 2000) are used for assimilation as variables describing model initial states. The second part is parallelization method based on a resource management and task partition strategy. We designed the algorithm, called DPPA (Dynamic Partition Points Algorithm for workload estimation), which is a portable technology for developing and deploying general-purpose Grid execution. DPPA aggregates the resource discovery-requirement match model into work load estimation algorithm, and empower standalone remote sensing retrieval models by decomposing the models with data parallel paradigm. This approach has several advantages. First, the partitioning provides a natural approach for low-level image processing. As we know, image processing generally involves some processes which are repeatedly applied to small set of neighbouring pixels within the image data structure. Second, the models retrieving information from remote sensed data usually use several spectral bands as input at one time. In this way, the cost of inter-processor communication can be reduced.
The remainder of the paper is structured as follows. Section 2 describes the methodology of AOT retrieval. Section 3 describes the design of algorithms used to deal with task partition, and a detailed description of DPPA algorithm for load-balanced parallelization. Section 4 introduces the implementation for high performance algorithms. Section 5 first describes the test-bed and data used in this study, and then presents the experimental results. Finally, Section 6 concludes with some remarks.

2. IMPLEMENTATION OF THE HIGH PERFORMANCE ALGORITHM ON GRID PLATFORM

2.1 Algorithm description

The algorithm determines that any of the 1×1 pixel sub regions (defined as 1 km × 1 km in size) can be classified as heterogeneous land, and the execution defaults to the SYNTAM model. As shown in Figure 1, a step-by-step approach of the retrieval workflow is described below.

1. The model starts with the setting up of geometric and processing parameters. Geometric parameters supply the longitude, latitude, sun and view zenith angles as well as azimuth angles. Processing parameters provide information about the atmospheric data, cloud mask, and AERONET ground-based data.

2. The next process of radiative calibration is applied, where the model converts instrument counts to top of the atmosphere reflectance.

3. Effects of spectral absorptions of water vapour, CO_2 and O_3 are fixed. The clouds and sun glint pixels are masked using the MODIS clear sky discriminating method.

4. AOT retrieval is an operational scheme comprises of ground station data assimilation and SYNTAM model.

5. After geometric correction and map projection, the step of mosaic is applied to stitch individual images in a larger composite, and remap the granules onto a latitude and longitude grid covering the China land.

6. The last step is finalizing the AOT product to permanent storage. When information of geophysical phenomena needs to be stored, the Hierarchical Data Format (HDF) format is used.

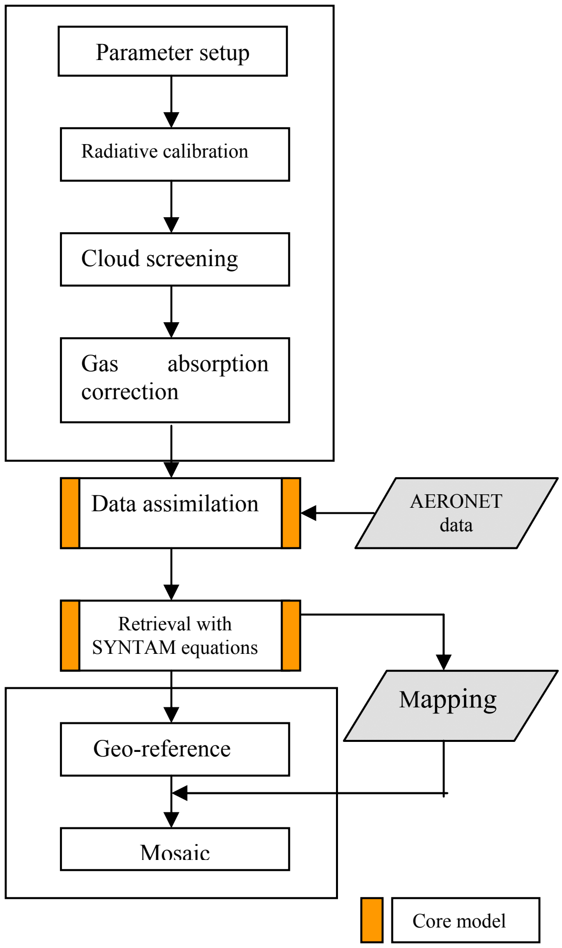

Figure 1. The flowchart of retrieval model

2.2 Task partition and scheduling

We consider this scenario: the Grid is de-centralized and managed by local scheduler and resource manager, having no limit as to number of nodes. Tasks are submitted for execution through a front-end submission node. No communication is assumed between nodes. Inner-mistakes like occasional faults, crashes, and other related events are handled by the local resource manager. Divisible load theory (Bharadwaj et al, 2003) is considered that jobs can be divided and sub-divided. Tasks use a standard Master-Worker paradigm to execute in parallelism where the master decomposes task, coordinates the actions of the workers, gathers the partial results from them and provides final results. To balance the workload of the nodes, each node should do an amount of work that is proportional to its speed. Therefore, two major goals of our partitioning algorithm are:

1. Obtain an appropriate set of workload fractions $\{a_i\} i \in (1, \cdots, P)$

2. Translate the chosen set of values into a suitable decomposition of the input data, taking into account the properties of the task.

First, we shall use a mathematical model that captures the realistic scenario to distribute the workload. The target Grid is heterogeneous, with p worker processes running on p processors labelled $P_1, P_2, \cdots, P_p$ .The affine communication cost is $g_i + a_i G_i$ for a message of size L , where G_i is the inverse of the bandwidth of the link between the master and P_i , and g_i is the latency. The affine computation cost is modelled as $o_i + a_i w_i$ for a load size a_i , where o_i start up time and w_i is processor cycle-time. We extended the theorem as follows (Beaumont et al, 2003):

First, when all elemental transfer times G_i are equal to G , sort the p processors so that $g_1 w_1 \le g_2 w_2 \le \cdots \le g_i w_i$. Then the ordering where tasks are sent to $P_1, P_2, \cdots, P_P$ is optimal.

Secondly, we use the Node Selection Method based on a general-purpose resource selection framework that provides necessary information about the Grid (Liu et al, 2002). This framework combines application characteristics and real-time status information to identify a suitable resource set. An extended ClassAds language (Raman et al, 1998) is used to express resource requests, and a method called set matching is used to identify suitable resources. The selection criteria are set according to processor local memory, disk space, Flops, and bandwidth.

Based on considerations stated above, we developed a Dynamic Partition Point Algorithm (DPPA).

Algorithm 1, Dynamic Partition Point Algorithm
Input: Image data I or parameters I.

Output: A vector of partition points P of input data or parameters.

1. Obtain the selected processor set using Node Selection framework. The number of available resources P and each node's identification number $\{p_i\} i \in (1, \cdots, P)$ are identified.
2. Calculate $a_i = \dfrac{(1/v_i)}{\sum_{i=1}^{P} (1/v_i)}$, $i \in (1, \cdots, P)$, to obtain the value of node portion.
3. Use the calculated values of $\{a_i\} i \in (1, \cdots, P)$ to produce P partitions of the input.

Data partition mode:

Using standard data portioning approaches (e g. spectral-domain or spatial-domain partitioning) separate data into P parts. Obtain a first partitioning of I so that the volume of data in each partition is proportional to the values of a_i .

Parameter partition mode:

Calculate possible combinations that cover the range of the parameter space I solely for the purpose of partitioning. The parameter combinations I are in general unknown but typically assumed to be one of N discrete cases.

2.3 Data partition

Two traditional standard approaches have been used for data partitioning in remote sensing: The first is Spectral-domain partitioning. This approach subdivides the multi-channel remotely sensed image into small blocks or sub-volumes, and each is made up of one spectral bands. The second is Spatial-domain partitioning. This approach subdivides the multi-channel image into slices, and each is made up of several contiguous spectral bands.
But in this work, we adopt the combination of first two strategies, in which the data is partitioned into blocks made up of spatially adjacent pixels which retain the full spectral band content associated to them. The data partitioning is described as follows. Consider an image of size $n \times n$, and p be the number of processors in Grid, **Block partition** is: The pixel vector (i, j) is allocated to processor $P_B(i, j)$, where, $B(i,j) = \left| j/n/\sqrt{m} \right| + \left| i/n\sqrt{m} \right|$, if $\left| j/n/\sqrt{m} \right|$ is even; $B(i,j) = \left| j/n/\sqrt{m} \right| \sqrt{m} + \left| j/(n/\sqrt{m}) \right| - \left| i/n\sqrt{m} \right|$, if $\left| j/n/\sqrt{m} \right|$ is odd. Vector (i, j) has k elements, representing the k bands as input.

2.4 Border handler and overlapping function

A data parallel paradigm is used to scale up to the number of runs that are desired in a Grid environment. An important issue in image processing operations is that accesses to pixels outside the spatial domain of the input image are possible. To implement a high efficient data parallel algorithm, we have to reduce data transfer/communication cost with a step further. An overlapping handling strategy is adopted when some of the pixel positions are outside the input image domain for one node in Grid. In this situation, both those pixels inside the image domain and a copied circle are read for input.

Apart from the strategy above to update overlapping parts of partial data, a function to handle border need to be implemented. The function decides when to use overlapping handling strategy or just fill outside border pixels with default values.

By consider border-handling and overlapping, extended types of partitioning is **Block-cyclic partition:** The pixel (i, j) is allocated to processor $P_{BC}(i)$, where $BC(i)$ is $(|i/b| + |j/b|)$ mod m, and b is a blocking factor indicating the number of elements to be packed in a block. Vector (i, j) has k elements, representing the k bands as input.

2.5 Load-balanced Parallel Retrieval Algorithms

We have implemented load-balanced retrieval SYNTAM model coupled with DPPA algorithm. The algorithm can be divided into six steps.

Algorithm 2, Parallel SYNTAM
Input: Image band I, initial parameter P, number of tasks N
Output: Set of AOT output O.

1. Data pre-process.
2. AERONET data are interpolated, projected, matched, and assimilated as Initial Parameter.
3. With DPPA algorithm to estimate workload on each node, the data are partitioned into small blocks and distributed to processors.
4. Paralleled computation with SYNTAM equations.
5. Collect results from nodes.
6. Spatial smoothing with the retrieved aerosol optical depth.

3. A CASE STUDY: AOT RETRIEVAL OVER CHINA

3.1 Data and test-bed

The image scenes used for experiments were collected by MODIS instrument, which covered China land. Each mosaic (geographic projection ,range 15° N -55° N, 70° E-135° E , spatial resolution 0.01° , data array 6501×4001) was selected from AQUA/TERRA database of daytime images, which consisted of 14 granules, 7 spectral bands and a total size of approximately 6.7 Gbytes. The data were acquired from the NASA Distributed Active Archive Centre. Volume of auxiliary data, e.g. the AERONET data, atmospheric data, and cloud masks (MODIS L35) are about 1.2 Gbytes.

We installed the application in a test-bed of computational Grid pool in the IRSA, CAS. We configure levels of the Grid. Level 1 is connected to the dedicated CPU server serving as database and invokes tasks directly without parallelization. Level 2 and Level 3 reside on submission machines connected to large size Grid pools. The pool of work stations are made up of commodity PCs in Table 2 256 Mbytes to 1 Gbytes. The network used to interconnect the nodes to nodes could be Ethernet 100 Mbits/sec. The operating systems used were Linux Red-Hat 9.0, Windows NT5.0, and Windows XP.

3.2 Experimental results

We successfully produced 4 GBytes of aerosol property products in under a 5-hour period. As for the computational performance, Table 2 shows the comparison of configurations between the sequential execution on an Intel P4-2.0 GHz computer and distributed execution on the Grid test-bed. The input data are partitioned into tasks of various sizes. For example, a task size of 197Mb regional granule image, or of 3940 Mb nationwide image will results in 4, 8, or 16tasks. Selection of task granularity and number of tasks determined by DPPA algorithm are important in load balancing and scalability experiments. Table 2 shows performance for varying number of tasks and sizes of input data. The execution time increases when the number of tasks is decreased due to insufficient number of tasks to keep all the processors occupied.

4. CONCLUSION

In this paper, we have discussed the design and implemetation of Grid-enabled high performance retreival model in a remote sensing AOT retrieval application. Specifically, we have presented several highly innovative parallel techniques for parameter assimilation, inversing computation of the AOT model, and implemented them on heterogeneous and massively distributed Grid platform. The experiments showed that we were able to process the whole image scene and retrieving AOT parameters with in 5 hours, and made it possible to apply the models over large area data covered by multiple scenes in a practical manner. Our study reveals that the combination of the computational power offered by Grid is likely to introduce new perspectives in the remote sensing systems for exploiting improvement of accuracy, productivity and performance of remote sensing quantatitive retrieval model.

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Dataset	Description	Type	Size
NASA satellite imagery	Several hundred scenes	HDF	5.6 Gbytes
MODIS cloud product data	Remote sensing auxiliary data	GeoTIFF	1.8 Gbytes
China geology	Geologic country map at 1:1,000,000 scale	Shapefile	300 Mbytes
Atmospheric data	China's precipitation, ozone, and CO2 data for June 2007	ASCII file	500 Mbytes
AERONET data	AERONET stations in China, 2007	ASCII file	60 Mbytes

Table 1. Earth science data used for AOT retrieval.

Data size (Mbytes)	Sequential time (min)	Number of task	Grid run time (min)	Speed up	Efficiency
197	413	4	118	3.5	0.875
		8	63	6.55	0.818
		16	39.7	10.4	0.658
		100	33	12.5	0.125
3940	5809	4	1826.6	3.18	0.79
		8	905	6.42	0.81
		16	414.9	14	0.87
		100	434	13.3	0.13

Table 2. Number and size of input files in reference to performance