VEGETATION INDEX MAPS OF ASIA TEMPORALLY SPLINED FOR CONSISTENCY THROUGH A HIGH PERFORMANCE AND GRID SYSTEM

Shamim Akhter¹, Kento Aida^{1,2} ¹Information Processing Department, Tokyo Institute of Technology, Japan

²National Institute of Informatics, Japan

Yann Chemin International Rice Research Institute (IRRI), Philippines

Keywords: NDVI, Remote Sensing, LMF, High Performance Computing, Grid.

Abstract: Vegetation Index Map provides the crop density information over a precise region. Remote Sensing (RS) images are at the basis of creating such map, while the decision-maker requirement stands for Vegetation Index Maps at various in-country administrative levels. However, RS image includes data noises due to influence of haze or cloud especially in the rainy season. Temporally Splined procedure such as Local Maximum Fitting (LMF) can be applied on RS images for ensuring the data consistency. Running the LMF procedure with single computer takes impractical amount of processing time (approx. 150 days) for Asia regional RS image (46 bands/dates, 3932 rows, 11652 columns). Importing the LMF on High Performance Computing (HPC) platforms provides with a time optimization mechanism, and LMF has been implemented in cluster computers for this very purpose. A single cluster LMF processing timing still did not perform within an acceptable time range. In this paper, the LMF processing methodology to reduce processing time by combining the parallelization of data and task together on multi-cluster Grids is presented.

1 INTRODUCTION

Vegetation Index Maps are useful for crop modelling such as crop acreage estimation (Xu et al. 2005), plant stress detection (Zarco-Tejada et al. 2004), global vegetation (Ochi and Murai,1995) etc. NDVI (Normalized Difference Vegetation Index) is the most commonly used vegetation index. NDVI uses a normalized difference of Visible and Near Infrared reflectance bands from RS satellite imagery. It monitors density and vigour of green vegetation growth.

The Local Maximum Fitting (LMF) algorithm was developed by (Sawada et al. 2001). LMF uses temporally splined procedure by combining the time series filtering and functional fitting for removing clouds, hazes and other atmospheric effects from time series data of each pixel and ensure the data consistency (Sawada et al. 2002). A parallel LMF has been approached and implemented (Akhter et al., 2007). However, that parallel LMF implementation still holds a computational resource scalability problem. Thus, LMF takes too long in its actual 1 CPU set up, and even on small clusters it is not feasible for processing large areas. Therefore, necessity arises for a new approach to process LMF with data distribution technology.

This paper first solves the scalability problem in cluster based parallel LMF and then removes the other LMF limitations by approaching two new LMF processing methodologies, row distribution and row column distribution, with cluster based parallel LMF. Additionally, a new methodology of the LMF procedure for Grid based parallel computing is also introduced in this paper for solving the large processing time problem.

Akhter S., Aida K. and Chemin Y. (2008).

VEGETATION INDEX MAPS OF ASIA TEMPORALLY SPLINED FOR CONSISTENCY THROUGH A HIGH PERFORMANCE AND GRID SYSTEM. In Proceedings of the Third International Conference on Software and Data Technologies - ISDM/ABF, pages 284-287 DOI: 10.5220/0001885902840287 Copyright © SciTePress

2 LMF THEORY

LMF has been used by many researches as a tool to remove the atmospheric effects from RS data, e.g., Nagatani et al. (2002), Sawada (2001), Shulian and Susaki (2006), Wada and Ohira (2004). Due to large processing time, an OpenMP based LMF has been implemented. Since multi computer based distributed systems (cluster and Grid) have a larger processing capacity for a lower cost, naturally, choice turns towards developing a parallel LMF procedure to run on distributed platforms. A cluster based parallel LMF procedure was approached and implemented in (Akhter et al. 2007).

The LMF is a time series processing which integrates the time series filtering and the fitting processing. Local Maximum Filtering is shown in Equation (1).

$$d'_{t} = Min \begin{bmatrix} Max(d_{t-w+1}, d_{t-w+2}, \cdots, d_{t}), \\ Max(d_{t}, d_{t+1}, \cdots, d_{t+w+1}) \end{bmatrix}$$
(1)

d_t: Observed data at time t, w is the filter window,

 d'_t is modified data at time t.

$$f_{t} = c_{0} + c_{1}t + \sum_{t=1}^{N} c_{2t} \sin\left(\frac{2 \prod k_{1} t}{M}\right) + c_{2t+1} \cos\left(\frac{2 \prod k_{1} t}{M}\right)$$
(2)

Here, c_i (i=0,1,2t,2t+1) are coefficient(s), t: Time, N: Number of time series data, M: Number of data for 1 cycle for each harmonic curve, e.g. M=36, means 36 images/year, k_i : Periodic function by assuming that six periods (1 month, 2 months, 3 months, 4 months, 0.5 year, 1 year) might be used e.g. {1, 2, 3, 4, 6, 12}. These six periodic functions are implemented during the initial step. Equation (2) is converted to the sin curve function.

$$f_{1} = c_{0} + c_{1}t + \sum_{i=1}^{n} \left\{ A_{i} \sin\left(\frac{2\prod k_{i}t}{M} + x_{i}\right) \right\}$$
(3)

Here, A_i is amplitude and x_i is phase lag of sine curve. In this study, we use these A_i and x_i parameters calculated from initial step of LMF processing. To remove the effects of clouds, hazes and system noises, the time-series filtering and the fitting processing are repeated until the optimum result functions are obtained. To avoid over-fitting, Akaike Information Criterion (AIC,2007) is used to choose limited numbers of independent variables in the model for stable prediction.

Serial LMF procedure is divided into three parts. (i) Pre LMF (pre-LMF), (ii) LMF procedure, (iii) Post LMF (post-LMF). Different temporal bands (date wise sorted) images are stacked together to one image and provided to LMF. The temporal band images (1, 2, ..., n) are stacked together and consider as a 3-D matrix, where Image columns= Xaxis, Image lines (rows) =Y-axis, and temporal bands=Z-axis. Only a single row from the 3-D matrix is extracted and placed into a 2-D matrix, where each column of 2-D matrix contains different band values for each column pixel from the extracted row (3-D matrix).This whole process is called pre-LMF. For each iteration, each column of that 2-D matrix, executes the LMF method.

For (Col 1, Col2 ,..., Col N) For (Row1, Row2 ,...,Row N) LMF (, , ,)

The calculated and processed pixel values are again written to the same column of the 2-D matrix and then placed in the 3-D matrix (as the same way they were extracted). This process after executing LMF is called post-LMF.

To make the LMF procedure parallel the pre-LMF and post-LMF processes are not modified. LMF procedure is broken down for simple units for parallelism. LMF process will work parallel by executing more than one column of that 2-D matrix at the same time.

3 IMPLEMENTATION SCHEMES AND EXPERIMENTAL RESULTS

Two different sizes (small and large) images were used for the purpose of these experiments. The small image was provided from (Chemin, Y., 2006). This is a concatenation image of 136 band images with dimensions of 38 rows and 37 columns. The large 8days aggregated images of MODIS (Moderate Resolution Imaging Spectroradiometer) were downloaded from (EDC, 2007). The large images were imported from HDF to GeoTiff by the help of a Unix shell script using a command-line tool from the Modis Reprojection Tool (MRT,2007). Eventually, the Geospatial Data Abstraction Layer tool (GDAL, 2007) was used to convert GeoTiff to ENVI format. Other processing on images were done with Dr. Honda's image handling library (HONDA, 2007). Different methodological approaches were also taken to increase the parallel efficiency as well as the working capability of LMF procedure.

3.1 Distribution Strategies on Cluster

The first approach is to remove the scalability problem from the cluster based parallel LMF

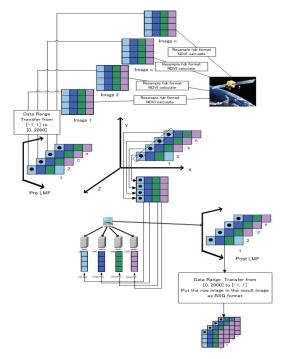


Figure 1: Row Distribution Cluster based Parallel LMF.

(Akhter et al., 2007). The improved MPI FORTRAN LMF code can now run with any number of

computing nodes. First, we processed LMF with small image (136 bands 38 rows and 37 columns) by implementing on a cluster with 22 computing nodes.

In Fig. 1, all the temporal images are individually processed as a LMF requirement. A script was developed to read each row from all temporal images and stack them together to form a row-image. Each row-image is then passed into the parallel LMF model for processing. However, increasing the column numbers will generate a software segmentation fault. This happens because of the data storing constraint inside the programming environment. A new and generic approach is then required.

As a result, both row-wise and column-wise distribution mechanism was implemented. In this methodology, all the temporal images in column direction are all virtually (programmatically) partitioned into a desirable block. The block window size (BWS) needs to be chosen according to the image data type. In our script, we used a threshold value (7000) for window size selection so that the column data will be equally distributed. Thus, from each column portion, each row of all temporal images will be merged together to become a row image and then processed by cluster based parallel LMF. The original MODIS data sample with 136 bands, 38 rows and 37 columns were used for

experiments. On a 16 nodes cluster testbed the highest speedup with cluster based LMF

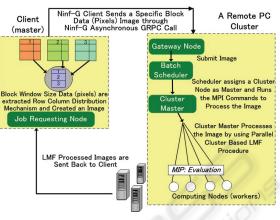


Figure 2: Grid based LMF Methodology.

(Akhter et al., 2007) was 4.11. Removing the scalability constrains from cluster based LMF gains the speedup to 16 with row based distribution. However, due to the additional communication overhead, the speedup with the generic row column based distribution approach (with BWS=2) falls to 8. Increasing computation nodes to the level, where the number of parallel task distribution meets or lower to the total row based. Additionally, the row column distribution technique is applied on a large image (46 bands, 3952 rows and 11952 columns) with parallel LMF (because it is more generic than others). The experiment processed only 20 rows on a 22 computing nodes cluster. It was traced that to process one row takes around 78 seconds. Thus, with cluster based computing, an image of 3952 rows will take around 308256 (3952x78) seconds, 3.57 days. This is still an unacceptable processing time. To increase the efficiency of the LMF processing time, large computational power is required and that can be provided by Grid computing technology.

3.2 Distribution Strategies on Grid

To increase the LMF runtime performance, a Grid based LMF implementation is required. The basic principle of this methodology is the hierarchical parallel implementation (Fig. 2). Where the Grid master node applies the row column distribution mechanism creating a row wise image and then sends that row-image to each cluster master for LMF processing. Each cluster master then uses the MPI based parallel LMF to process the row image in distribute manner with the help of its worker nodes. After completing the LMF process, the cluster master sends back the result image to Grid master. Grid master then stores the processed image segment to its output image and it continues again. The Grid master uses GridRPC calls (Nakada, H. et al, 2002) for distributing image to cluster master and that calling mechanism is implemented on the Ninf-G (Takada, Y. et al, 2003) programming framework.

4 CONCLUSIONS

In this paper, several approaches were explained to improve the parallel cluster based LMF, so that it runs on large dimensional RS image. Two different data distribution mechanisms, the row distribution and the row column distribution, were successfully implemented and their timing behaviour was compared. Although row column distribution takes the highest timing among three cluster based parallel LMF approaches, it is the most generic approach for LMF processing and fruitfully applied in the large RS image LMF processing. The accuracy of the new methodologies was traced and compared with previous LMF outputs and the level of accuracy was 100%. Full automated script was developed that helped the user (without vast knowledge in RS) to process their application easily with LMF system. Due to the large processing time, LMF is required to implement in Grid testbed. A Grid based implementation methodology was proposed with the new LMF data distribution technique. In near future, the authors plan to evaluate the Grid based LMF performance. A web based portal is required for supporting online LMF processing service. Additionally, the authors also plan to examine crop calendar pattern through LMF process.

REFERENCES

- AIC,2007,http://en.wikipedia.org/wiki/Akaike_informatio n criterion)
- Akhter, S., Sarkar, I., Rabbany, K. G., Akter, N., Akhter, S., Chemin, Y., and Kiyoshi, H., 2007, Adapting the LMF Temporal Splining Procedure From Serial toMPI/Linux Clusters, *Journal of Computer Science 3* (3): 130-133, ISSN 1549-3636, © 2007 Science Publications.
- Chemin, Y., and Honda, K., 2006, Spatio-temporal fusion of rice actual evapotranspiration with genetic algorithms and an agro-hydrological model, *IEEE Transactions on Geoscience and Remote Sensing*, Vo.44, No. 11, pp.3462-3469.

- EDC (Eros Data Centre), 2007, (http://edcimswww.cr.usgs.gov/pub/imswelcome/).
- GDAL, 2007: http://www.remotesensing.org/gdal/)
- HONDA, 2007: (http://rslultra.star.ait.ac.th/~honda/ textbooks/advdip/utilHonda.zip).
- MRT,2007:http://lpdaac.usgs.gov/landdaac/tools/modis/)
- Nagatani, I., Saito, G., Toritani, H., and Sawada, H., 2002, Agricultural Map of Asia Region Using Time Series AVHRR NDVI Data, *Proceedings Online of the 23rd Asian Conference on Remote Sensing*, 25-29 November 2002, Birendra International Convention Centre in Kathmandu, Nepal. Available online at: http://www.gisdevelopment.net/aars/acrs/2002/pos2/1 84.pdf
- Nakada, H., Matsuoka, S., Seymour, K., and Dongarra, J., 2002, GridRPC: A Remote Procedure Call API for Grid Computing, GWD-I (Informational), Advanced Programming Models Research Group, http://www.eece.unm.edu/~apm/docs/APMGridRPC07 02.pdf, July 2002.
- Ochi, S., and Murai, S., 1995, Monitoring Global Vegetation Degradation Using NOAA NDVI Data, Proceedings of Asian Conference of Remote Sensing 1995.
- Sawada, H., Sawada, Y., Nagatani, I., and Anazawa, M., 2001. Proceeding for the 1st regional seminar on geoinformatics for Asian eco-system management.
- Sawada, H. and Y. Sawada, 2002. Modeling of vegetation seasonal change based on high frequency observation satellite. *Environmental Information Science Papers*. Vol. 16.
- Shulian, N., and Susaki, J., 2006, Detection of Agricultural, Drought in Paddy Fields using NDVI from MODIS Data: A case study in Burirum Province, Thailand, Proceedings. *Proceedings of International Geoscience and Remote Sensing Symposium* (IGARSS2006), pp. 4076-4079, Aug, 2006
- Tanaka, Y., Nakada, H., Sekiguchi, S., Suzumarn, T., and Matsuoka, S., 2003, Ninf-G: A Reference Implementation of RPC –based Programming Middleware for Grid Computing. Journal of Grid Computing, Vol.1, 41-51.
- Wada, Y., and Ohira, W., 2004, Reconstructing Cloud SPOT/Vegetation Using Harmonic Analysis with Local Maximum Fitting, 25thACRS2004, Chiang mai, Thailand.
- Xu. W., Huang, J., Tian, Y., Zhang, Y., and Sun, Y., 2005, A method of estimating crop acreage in large-scale by unmixing of MODIS data, *Geoscience and Remote Sensing Symposium, IGARSS '05. Proceedings. 2005 IEEE International* Volume 4, Issue , 25-29 July 2005 Page(s): 2987 – 2990.
- Zarco-Tejada, P.J., Berjón, A., and Miller, J.R., 2004, Stress Detection in Crops with Hyperspectral Remote Sensing and Physical Simulation Models, *Proceedings* of the Airborne Imaging Spectroscopy Workshop -Bruges, 8 October 2004.