SERVICES FOR SATELLITE DATA PROCESSING

Andriy Shelestov, Oleksiy Kravchenko, Michael Korbakov

Abstract: Data processing services for Meteosat geostationary satellite are presented. Implemented services correspond to the different levels of remote-sensing data processing, including noise reduction at preprocessing level, cloud mask extraction at low-level and fractal dimension estimation at high-level. Cloud mask obtained as a result of Markovian segmentation of infrared data. To overcome high computation complexity of Markovian segmentation parallel algorithm is developed. Fractal dimension of Meteosat data estimated using fractional Brownian motion models.

Keywords: cloud mask, fractals, Meteosat, Markov Random Fields, fractional Brownian motion, parallel programming, MPI.

ACM Classification Keywords: I.4.6 Image Processing and Computer Vision: Segmentation – Pixel classification, G.1.2 [Numerical Analysis]: Approximation – Wavelets and fractals, D.1.3 Programming Techniques: Concurrent Programming – Parallel programming, I.4.7 Image Processing and Computer Vision: Feature Measurement – Texture

Introduction

Among the variety of artificial Earth satellites geostationary satellites stand out due to their unique capability to observe Earth in a high frequency manner. The achievement of similar temporal characteristics using low orbit satellite platform could be possible only with a fair amount of satellites. However geostationary satellites suffer from two main drawbacks – low spatial resolution and relatively small amount of spectral bands. By these circumstances it is common to use geostationary satellites in the investigation of global Earth processes especially in the field of meteorology.

In this paper three services for geostationary satellite data processing are described. These services are designed to process data of Meteosat satellite that is operated by EUMETSAT international organization and provides information for solving practical meteorological problems. This satellite's onboard equipment makes one image of earth disk in 30 minutes in three spectral bands – visible (VIS), infrared (IR), water vapour (WV). Developed services include preprocessing service of noise detection and reduction, service for cloud mask extraction and high-level service for fractal features estimation.

Although noise reduction as preprocessing step is obviously important for further processing one of the most useful satellite data products is cloud mask. It can be used in a standalone way in applications such as air flights and satellite photography planning. Also it can be used as an input data for various satellite data processing algorithms like Normalized Difference Vegetation Index (NDVI), Sea Surface Temperature (SST) and operational wind vectors maps extraction, or even more complex applications such as numerical weather models.

A common approach for cloud mask extracting is using of multi- and hyperspectral satellites providing data in many spectral bands. Basing on information about radiance intensities a conclusion about cloudiness can be made on per pixel basis. For instance, this approach is widely used for processing of multispectral AVHRR and MODIS data. But three spectral bands of Meteosat do not provide enough information for multispectral cloud recognition algorithms operating on per pixel basis. This causes the need for algorithms, which involves temporal and spatial dependencies in data processing. One of such algorithms is a Markov Random Field segmentation, which allows determining pixel's class with regard to its neighborhoods. Markovian approach allows taking into account different possible distributions of intensities per class and do not introduce global parameters such as thresholds, which is often used in multispectral data processing.

To extract high-level meteorological features fractal approach is used. Meteosat data is modeled by fractional Brownian motion process. Approximation with self-affine fractal allows estimating local fractal dimension of Meteosat image. For this problem Fourier estimator is considered.

Data Preprocessing

Meteosat images come with a lot of noise of two sorts. The first one is the so-called "salt and pepper" noise consisting of noisy pixels uniformly distributed over image. The second one is the impulse burst noise, which distorts images with horizontal streaks of few pixel heights filled with white noise.

In the Space Research Institute NASU-NSAU algorithm for detecting and removing such noise was developed [Phuong, 2004]. On the first step of this algorithm noise streaks is detected and removed by cubic spline interpolation method. During the second step the "salt and pepper" noise is detected by modified median filter and removed by using bit planes approach. The algorithm based on this approach separates an image in 256 planes with binary values. After that, each of these planes is processed separately in order to remove noise.

Cloud Mask Extraction

Following Markovian approach the image is represented as a $n \times m$ matrix of sites S. The neighborhood of site s_{ij} is any subset $\partial_{ij} \subset S$, such that $s_{ij} \notin \partial_{ij}$. With each site s_{ij} two random variables are associated – an intensity X_{ij} (as usual it takes integer value in interval [0; 255]) and a hidden label Y_{ij}. The specific values the random variables take are denoted x_{ij} and y_{ij} respectively. So two sets of variables defined for image S: $X = \{X_{11},..., X_{nm}\}$ and $Y = \{Y_{11},...,Y_{nm}\}$.

Markov Random Fields (MRFs) are widely used for image segmentation [Li, 1995]. With the Hammersley-Clifford theorem the equivalence of MRF and statistical physics Gibbs models was proved [Li, 1995]. This theorem gives us the equation for probability of specific segmentation $P(Y)$

$$P(Y) = \frac{1}{z} e^{\beta V(Y)} = \frac{1}{z} e^{\beta \sum_{i,j} V_{ij}\left(\partial_{ij} \cap \{y_{ij}\}\right)} \qquad (1)$$

In this equation, z is normalizing constant necessary for holding the condition $\sum_Y P(Y) = 1$. β denotes the image correlation parameter. V is the so-called potential function. Its structure is highly coupled with optimal segmentation of MRF. Defining a particular potential function it is possible to model physics features of segmentation. The right part of equation shows that potential function V can be represented as a sum of potentials defined at each site: $V = \sum_{i,j} V_{ij}$.

For the cloud mask extraction problem the following Markovian model was used: the observed intensity X_{ij} depends only on local label Y_{ij} and a conditional distribution of random variable X_{ij} is Gaussian. The Bayes' theorem about a priory and a posteriori probabilities' relation yields a complete model of intensities and labels coupling [Shiryaev, 1989]:

$$P(Y \mid X) \propto P(X \mid Y)P(Y) = \frac{1}{z}\exp\left\{\sum_{i,j} \beta_{ij} n_{ij}\left(y_{ij}\right)\right\} \times \prod_{i,j} \frac{1}{\sqrt{2\pi}\sigma_{ij}} \exp\left\{-\frac{1}{2\sigma_{ij}^2}\left(x_{ij} - \mu_{ij}\right)^2\right\} \qquad (2)$$

Here σ_{ij} and μ_{ij} are a standard deviation and a mean of random variable X_{ij} , n_{ij} is the number of pixels in neighborhood ∂_{ij} with the label equal to Y_{ij} .

The goal of segmentation is to maximize $P(Y \mid X)$ under particular intensities X . This corresponds to obtaining maximum for a posteriori label's estimate:

$$Y : Y^* = \arg\max_y \{P(Y \mid X)\}. \qquad (3)$$

Results of clouds segmentation and corresponding cloud borders are shown at the fig.1.

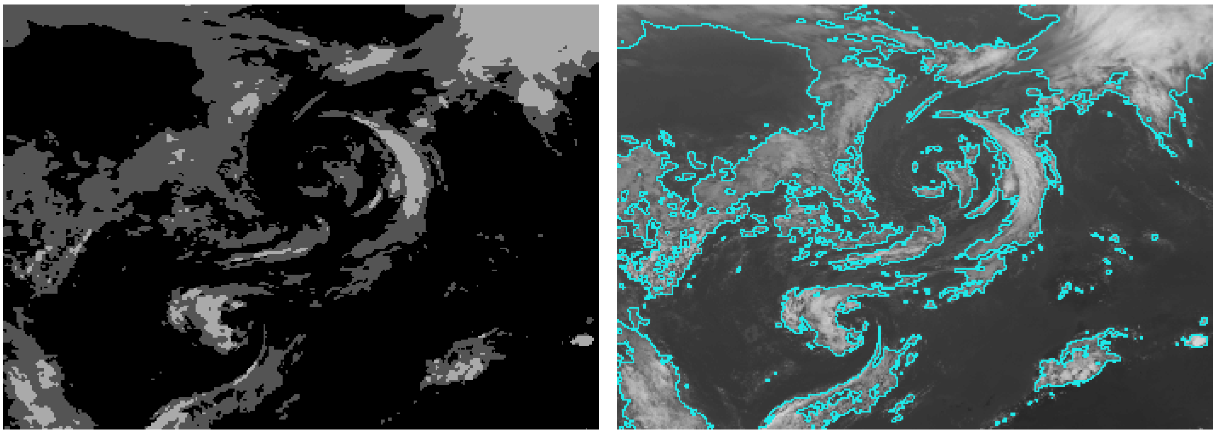


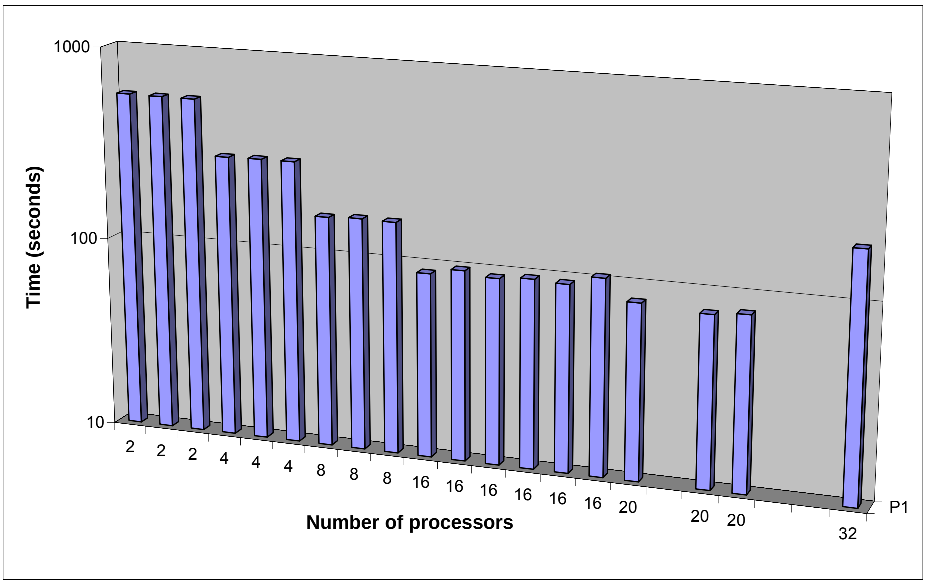
Fig. 1 .MRF segmentation result and corresponding cloud borders.

Parallel Execution Results

High computational complexity of Markovian segmentation algorithm together with large sizes of satellite images determines the need for parallel realization of cloud mask extraction process.

Meteosat image filtering and Markovian segmentation algorithms were implemented using MPI parallel programming interface [MPI, 1997]. Due to locality of dependencies in Markovian image model, it is possible to divide image into almost independent rectangular parts. Then each of these parts is processed by different computational node. Synchronization of several global per-class parameters and image part's borders is performed by means of MPI's group communication functions.

The program was run on the cluster of Institute of Cybernetics NASU consisting of 32 Intel Xeon processors. It has demonstrated good level of parallel acceleration giving almost proportional speed boost with increase of number of computational nodes used (fig. 2). Processing time increasing and productivity slowdown for 32 processors is related with large amount of interprocessors' data transfer, which is fulfilled in sequential way (due to architecture of parallel machine). So according to experimental results the most preferable number of processors for this task is 20. This information is important for load balancing.



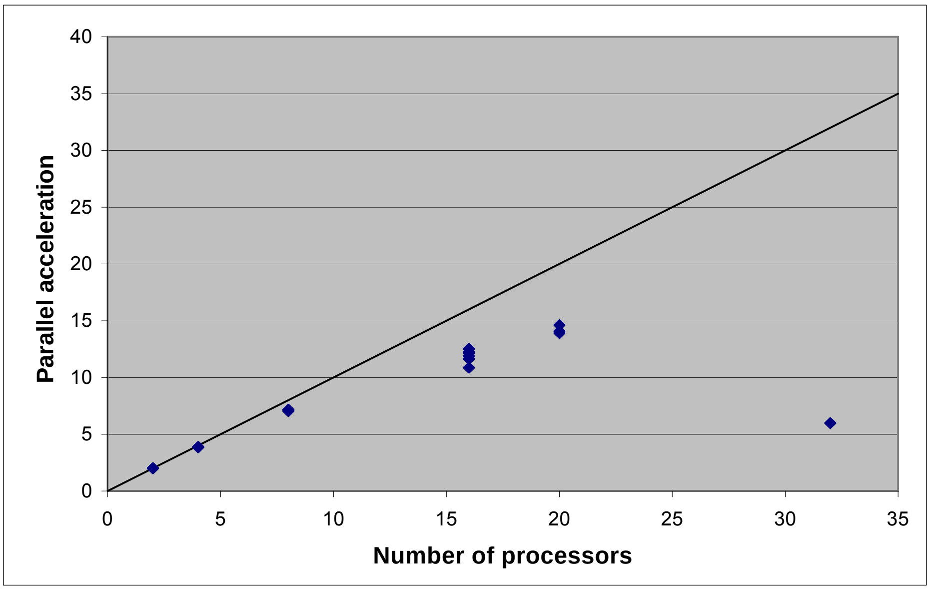


Fig. 2. Performance evaluation of parallel MRF segmentation algorithm.

Fractal Features Extraction

To estimate fractal dimension of Meteosat data water-vapour images are modeled by fractional Brownian motion (FBM) process. Fractional Brownian motion process is the generalization of plain Brownian motion process with expected squared difference in intensity of any two pixels being proportional to the powered distance between the pixels. In the case of two dimensions it is described by the following equation [Potapov, 2002]:

$$\mathbf{E}\left|I(x,y)-I(x+\Delta x,y+\Delta y)\right|^2 \sim \left|\Delta x^2+\Delta y^2\right|^H, \tag{4}$$

where $I(x,y)$ – is the intensity of pixel with coordinates (x,y),

$0 < H < 1$ – is the Hurst coefficient.

The case of $H = 1/2$ corresponds to classical Brownian motion.

It can be shown that two-dimensional FBM process has a Fourier power spectrum

$$\mathbf{E}\left|F(f)\right|^2 \sim 1/f^{\beta}, \tag{5}$$

where the power exponent β, the Hurst coefficient H and fractal dimension D are determined by the following equations:

$$\beta = 2H+2, \; D = 3-H \tag{6}$$

Thus knowing β parameter we can estimate the Hurst coefficient H and fractal dimension D.

To examine our algorithm for fractal dimension estimation synthesized images were used. To generate fractional Brownian motion on a two-dimensional grid we use fast Fourier transform filtering. This procedure generates an initial image I_0 as a set of independent Gaussian random variables, $I_0(x,y) \sim N(0,1)$. Then a discrete Fourier transform is applied to image I_0, thus obtaining the grid of Fourier coefficients:

$$F_0(k_x,k_y) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} I_0(x,y)\exp\left\{-2\pi i\frac{xk_x+yk_y}{N}\right\}, \; k_x,k_y = \overline{1,N} \tag{7}$$

The second step consists in construction of new Fourier coefficients $F_1(k_x,k_y)=F_0(k_x,k_y)\Big/\left|k_x^{\ 2}+k_y^{\ 2}\right|^{\frac{\beta}{4}}$.

At last the inverse Fourier transform is applied to $F_1(k_x,k_y)$ coefficients forming result image I_1.

Modeling results for different values of Hurst coefficient H and fractal dimension D from (6) are shown at fig. 3.

a) b) c)

Fig. 3. The examples of FBM generation

a – $H=0.4$, $D=2.6$; b – $H=0.7$, $D=2.3$; c – $H=0.9$, $D=2.1$

Fractal features extraction algorithm based on local Fourier power spectrum investigation. Whole Meteosat image is processed by moving window and corresponding image part used to calculate local Fourier coefficients $F(k_x,k_y)$. According to (5) these coefficients are used to estimate index of power approximation from a linear fit to data $\left\{\left(\log\left|F_1(k_x,k_y)\right|,\log\left|k_x^{\ 2}+k_y^{\ 2}\right|\right),k_x,k_y=\overline{1,N}\right\}$.

This approach was applied to Meteosat data processing, specifically for fractal dimension detection after cloud mask segmentation. It allows to determine areas of turbulence and to detect sources of some meteorological disasters. Results of satellite data processing are shown at fig. 4.

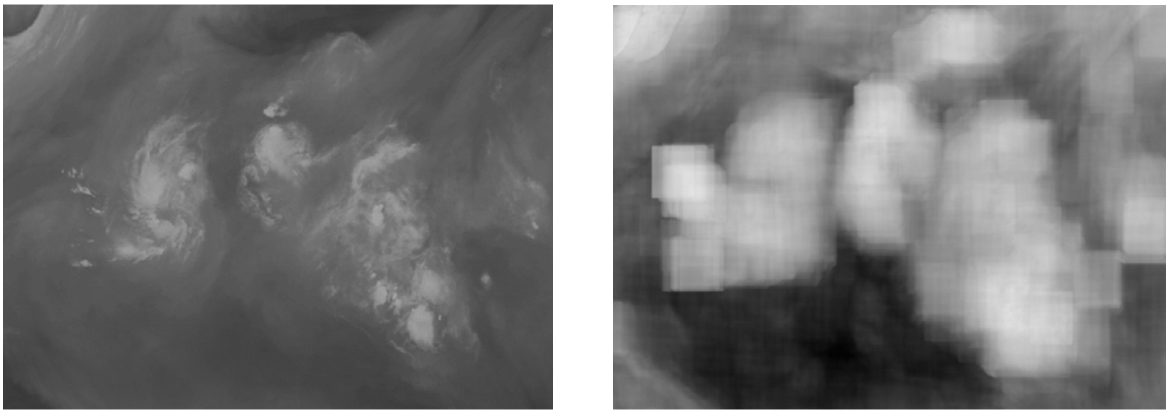


Fig. 4. Original WV image and corresponding fractal dimension estimation.

Conclusions and Further Works

Markovian approach has showed its effectiveness in the task of cloud mask extraction from Meteosat satellite data. Also parallel Markovian segmentation algorithm performed very well exploiting locality of Markovian image model. After cloud mask construction one can implement any other algorithm of higher level satellite data processing. One of them is fractal dimension detection. It allows to determine areas of turbulence and to detect sources of some meteorological disasters.

Further works includes services implementation in GRID environment, which will connect computational cluster and other computational resources with satellite data archives. GRID infrastructure will allow to integrate data processing algorithms with datasets and to provide access to computational tools and there results (products and services) for wide area of users. This kind of investigation is actively carrying out in Space Research Institute of National Academy of Sciences and National Space Agency of Ukraine.

Bibliography

[Phuong, 2004] N. T. Phuong. A Simple and Effective Method for Detection and Deletion of Impulsive Noised Streaks on Images. Problems of Controls and Informatics, 2004. (in Russian)

[Li, 1995] S.Z. Li. Markov Random Field Modeling in Computer Vision. Springer-Verlag, 1995.

[Shiryaev, 1989] A. N. Shiryaev. Probability. Nauka, 1989. (in Russian)

[MPI, 1997] MPI-2: Extensions to the Message-Passing Interface. University of Tennessee, 1997

[Potapov, 2002] A. A. Potapov. Fractals in radiophysics and radiolocation. Logos, 2002. (in Russian)

Authors' Information

Andriy Shelestov, PhD. – senior scientific researcher, Space Research Institute NASU-NSAU, 40 Glushkova St., 03680 Kyiv, Ukraine, e-mail: shelest@dialektika.com

Oleksiy Kravchenko BSc.– system developer, Space Research Institute NASU-NSAU, 40 Glushkova St., 03680 Kyiv, Ukraine, e-mail: akm3000@mail.ru

Michael Korbakov BSc.– system developer, Space Research Institute NASU-NSAU, 40 Glushkova St., 03680 Kyiv, Ukraine, e-mail: rmihael@ukr.net

FORMAL DEFINITION OF ARTIFICIAL INTELLIGENCE [1]

Dimiter Dobrev

Abstract: A definition of Artificial Intelligence (AI) was proposed in [1] but this definition was not absolutely formal at least because the word "Human" was used. In this paper we will formalize the definition from [1]. The biggest problem in this definition was that the level of intelligence of AI is compared to the intelligence of a human being. In order to change this we will introduce some parameters to which AI will depend. One of this parameters will be the level of intelligence and we will define one AI to each level of intelligence. We assume that for some level of intelligence the respective AI will be more intelligent than a human being. Nevertheless, we cannot say which is this level because we cannot calculate its exact value.

Keywords: AI Definition, Artificial Intelligence.

ACM Classification Keywords: I.2.0 Artificial Intelligence - Philosophical foundations

Introduction

The definition in [1] first was published in popular form in [2, 3]. It was stated in one sentence but with many assumptions and explanations which were given before and after this sentence. Here is the definition of AI in one sentence:

AI will be such a program which in an arbitrary world will cope no worse than a human.

[1] This publication is partially supported by the KT-DigiCult-Bg project