RESOLUTION ENHANCEMENT OF GERB DATA

L. Gonzalez, A. Hermans, S. Dewitte, A. Ipe, G. Sadowski, N. Clerbaux.

Remote Sensing from Space
Royal Meteorological Institute of Belgium (RMIB)
3, av. Circulaire, 1180 Bruxelles, Belgium

ABSTRACT

The Geostationary Earth Radiation Budget (GERB) project mission is to estimate accurate top of the atmosphere radiation budget at high temporal and spatial sampling. In order to reach this goal, the combination of the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument -with high spatial sampling rate- and the GERB instrument -with spectral broad band measurements and on-board short-wave calibration- is necessary.

Unfortunately, the GERB instrument has a low spatial sampling. Taking the advantages of each instrument, it is expected to have very accurate values with high spatial sampling. The processing developed can be divided in two steps. First, the SEVIRI data is compared to GERB data. For a correct comparison, the compared values must be of the same kind. The GERB broad band is estimated from the SEVIRI narrow-bands. A down-sampling, an interpolation in time and space are applied to fit the GERB acquisition time, spatial resolution and geolocation. The comparison of the real GERB data and the GERB data estimated from SEVIRI measurements defines correction factors to apply to the SEVIRI data. But these correction factors are at GERB spatial resolution. So the second step is the up-sampling of the correction factors. For coherent data, the application of the first step on the corrected SEVIRI should give the original GERB data (coherence criteria). The proposed poster is about the method developed for this up-sampling.

The problem is under-determined. There are more unknowns than equations to solve. These equations are the coherence criteria explain before. Furthermore, the correction factors depend on the viewed scene and are expected to be slowly varying on a specific scene. The problem can be seen as an optimisation problem (smooth variation for the correction factors) under constraints (coherence criteria). The method, the results on simulated data and the conclusions are exposed.

1. INTRODUCTION

On board the Meteosat Second Generation (MSG-1) satellite, the GERB instrument [1] will provide short- and long-wave spectral broadband radiation measurements of the Earth. The on board black body and solar diffusing sphere allow good calibration [2].

The GERB project mission, produced by a European consortium led by the UK together with Belgium and Italy, intends to estimate accurate top of the atmosphere radiation budget at high temporal and spatial sampling.

2. RMIB GERB GROUND SEGMENT PROCESSING

The RMIB takes part into the ground segment processing implementation. Its mission is to compute unfiltered radiances and to estimate solar and thermal fluxes. [3]
In order to reach maximal accuracy and maximal high resolution, GERB data will be combined with SEVIRI instruments data.
On the one hand GERB, thanks to its on-board calibration [2], provides well-calibrated short wave and long wave broadband radiances. But has as drawback a low spatial sampling. On the other hand, SEVIRI has a higher spatial resolution, its narrow band channels allow good scene identification [4] and hence solar and thermal fluxes estimations based on Angular Dependency Models (ADM) [5]. But its short wave measurements accuracy is less reliable, because SEVIRI has no on-board short wave calibration source.

The RMIB GERB ground segment processing intends to combine advantages of both instruments. It is divided in 3 steps:

First, estimations of broad band radiances and fluxes are derived from SEVIRI narrow band measurements [4].

Secondly, the SEVIRI–based radiances and flux estimations are corrected or re-calibrated by comparison with the well calibrated GERB measurements.
For a correct, coherent comparison, GERB and SEVIRI derived data must match in time and location, must be co-registered in space and time. Time interpolation, space interpolation and down sampling are applied to SEVIRI based data such that it fits the GERB acquisition time, spatial resolution and geolocation. The down sampling is computed by integration over each GERB pixel area of the SEVIRI resolution value convoluted by the GERB pixel Point Spread Function (PSF). From the comparison between the SEVIRI based radiance estimation co-registered at GERB time, resolution, and geolocation, and the GERB measurements, we compute spectral correction factors. Then, these correction factors are applied to the SEVIRI based flux estimates to produce better calibrated flux estimations. At the end of the second step, the process outputs well calibrated radiances and fluxes at GERB resolution [7].

The third step of the RMIB process, the purpose of this paper, is called the Resolution Enhancement (RE) processing and is aiming to improve the spatial resolution of the fluxes produced at step two.

3. RESOLUTION ENHANCEMENT PROBLEM

The purpose of the RE processing is to up-sample the accurate fluxes computed at GERB footprint resolution (nominally 50km x50km at nadir), to a 3*3 SEVIRI footprint resolution (nominally 9 km x 9 km at nadir).

Let's denote:

- (i,j) GERB (i.e. low resolution) pixel coordinates,
- (x,y) SEVIRI (i.e. high resolution) pixel coordinates,
- $F_{LR}(i,j)$ the low resolution GERB L2 flux,
- $\tilde{F}_{HR}(x, y)$ the high resolution SEVIRI-based flux estimates,
- $P_{i,j}(x, y)$ the Point Spread Function (PSF) at SEVIRI pixel (x,y) according to GERB pixel (i,j).

In the ideal case, the down sampling of the high resolution measurements, weighted by the PSF, should reproduce the low resolution measurement. We should have:

$$F_{LR}(i, j) = \sum_x \sum_y \left[P_{i,j}(x, y)\, \tilde{F}_{HR}(x, y) \right]$$

In a real case, this identity is not verified, mainly because the spectral modelling errors, the calibration quality and the spatial sampling rate of both instruments GERB and SEVIRI are different. The aim of the RE processing is to find correction factors c(x,y) to the high resolution SEVIRI-based flux estimates $\tilde{F}_{HR}(x, y)$, so that the integration of the corrected flux estimates does reproduce the low resolution
GERB L2 flux $F_{LR}(i,j)$. At each GERB pixel (i,j), the so-called coherence condition should be satisfied:

$$F_{LR}(i, j) = \sum_x \sum_y \left[P_{i,j}(x, y)\, c(x, y)\, \tilde{F}_{HR}(x, y) \right] \qquad \text{(Coherence Condition)}$$

If we denote by G^2 the number of GERB pixels (i,j), and by S^2 the number of high resolution pixels (x,y), we get a system of G^2 linear equations in the S^2 unknowns c(x,y). Since there are more unknowns than equations, the problem is under-determined. In order to obtain a practical solution, different strategies were designed.
One approach was to convert the equation set into a determined system. We reduced unknowns number to G^2 (i.e. one unknown correction factor per GERB pixel) by imposing on correction factors c(x,y) to be interpolated values of the GERB resolution correction factors. From a theoretical point of view, the resulting determined system has one solution and can be solved by matrix inversion. But from a practical point of view, full storage and explicit inversion of matrix M is inconceivable, moreover our tests to solve the system using iterative scheme were unsuccessful.
Then, we tried to see the problem from an other point of view.

4. OPTIMISATION UNDER CONTRAINTS

The correction factors are expected to depend on the viewed scene and to be slowly varying on a specific scene. We can then assume and impose as extra condition to the correction factors c(x,y) that they vary smoothly.
Following this idea, the problem can be seen as a minimisation of function under constraints. The function to minimise is an estimation of the roughness of the correction factors c(x,y). And the constraints are the coherence conditions, the identities between the down sampling of the high resolution corrected flux estimates and the low resolution or GERB flux. We choose as roughness estimation function to compare each correction factor to the mean of its 8 neighbours:

$$R\left[c(x,y)\right]=\frac{1}{2}\sum_{x,y}\left[c(x,y)-\frac{1}{8}\sum_{\substack{k,l=-1,0,1\\(k,l)\neq(1,1)}}\left(c(x+k,y+l)\right)\right]$$

This function is numerically minimised, under the coherence constraints, using an iterative scheme based on gradient calculation of the Generalised Lagrange Function [9]:

$$\Lambda(c,r)=R(c(x,y))+r\sum_{i,j}\left(E(i,j)\right)^2$$

where $E(i,j)=\sum_x\sum_y\left[P_{i,j}(x,y)\,c(x,y)\,\tilde{F}_{HR}(x,y)\right]-F_{LR}(i,j)$ is the coherence constraint at pixel (i,j)

r is a balance factor.

The iterative scheme equation is: $c^{k+1}(i,j)=c^{k}(i,j)-\alpha\frac{\partial\Lambda(c,r)}{\partial c(i,j)}$

The parameter α defines the scale of the correction step and therefore the choice of its value is of pre-eminent concern for the success of the iterative process [10]. The iterative process is stopped, meaning the updating values c^{k+1} are estimated close enough from solution, when the 2 following criteria are valid:

1. Smoothing test :

$$e_R=\sqrt{\frac{\sum_{x,y}\left[c(x,y)-\frac{1}{8}\sum_{\substack{k,l=-1,0,1\\(k,l)\neq(1,1)}}\left(c(x+k,y+l)\right)\right]^2}{\text{number\_of\_pixels}}}<e_R^{required}=0.001$$

   This criterium forces the correction factors to vary smoothly (i.e. Each c(x,y) has to be close to the mean of its 8 neighbours)

2. Test on coherence constraint :

$$e_E=\mathrm{Max}_{\forall i,j}\left|E(i,j)\right|<e_E^{required}=0.01.\frac{\text{Maximal flux value}}{2}$$

5. TESTS

The RE program was developed and tested in several stages.
First, the appropriateness of the Lagrangian iterative optimisation method to solve such resolution enhancement was checked on a simplified problem.
Secondly, the algorithm was validated and improved on more realistic configurations.

At the first testing stage, time and geolocation interpolations were avoided. 2 images (one a high resolution, the other at low resolution) representing the same scene of random rectangles were generated. The low resolution image was generated by down sampling of the high resolution image using a window average as a simplified approach of PSF convolution.
These simplified configurations allow us to test different forms of Generalised Lagrange function and several minimisation iterative schemes. We pointed out some drawbacks in term of stability and scalability, that could be reduced thanks to appropriate parameter values choice.

Starting from this successful simplified RE approach, we gradually complicated testing configurations and algorithms. More realistic radiances and flux scenes were generated using Meteosat 7 data. Images at real GERB and SEVIRI scale were used. PSF were randomly computed, slightly different according to different GERB detectors.

At the last stage, we generated, from Meteosat 7 measurements, ideal flux images scaled at SEVIRI/3 resolution (i.e. the high resolution we would like to reach). From these ideal configurations, GERB flux images are simulated by PSF down sampling while SEVIRI flux images -with small calibrations perturbations- are simulated by applying perturbation factors.

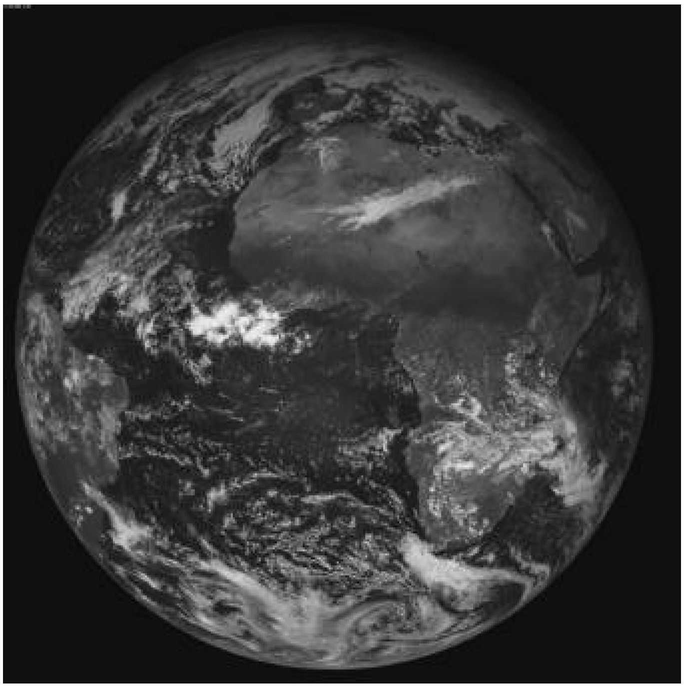

Figure 1 : Example of simulated SEVIRI image

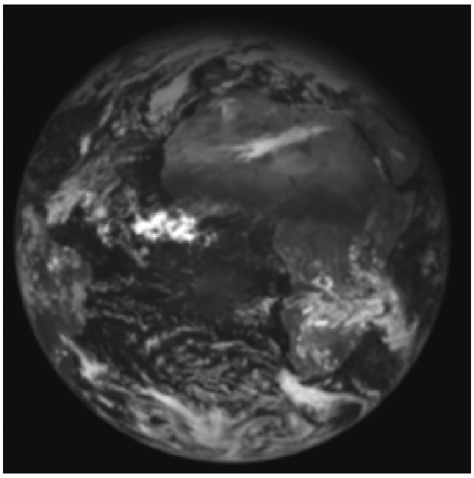

Figure 2 : Example of simulated GERB image

We generated 3 types of perturbation factor fields (referenced by case 1,2,3 in table 1): In case 1, fluxes are perturbed by a factor constant according to scene identification. In case 2, fluxes are perturbed by a factor that varies linearly with reference radiances values. In case 3, fluxes are perturbed by a factor that is a sinusoidal function of the reference radiances values. We also vary the perturbation amplitude. (10% of perturbation means factors vary between 0.9 and 1.1; 20% of perturbation means factors vary between 0.8 and 1.2;…)
Using as input these simulated GERB and SEVIRI images, the RE algorithm performances to retrieve reference fluxes image were tested and improved.

In order to find a good compromise between getting results as accurate as possible (i.e. approach the reference flux image as close as possible) and keeping computing time and memory requirement below reasonable a threshold, we refined the selection of parameters values, and hence stop criteria of iterative scheme.
For instance, we spent lot of time to choose a well fitted balance factor r. On the one hand, if r is chosen too small, the convergence speed is much too slow, on the other hand, if r is too big the problem becomes ill conditioned and generates numerical difficulties.

Perturbation case	% of perturbation	Number of iterations	CPU Time (*)	$\varepsilon_E(0)$	$\varepsilon_E(end)$	$\varepsilon_R(0)$	$\varepsilon_R(end)$
1	10 %	2	48 s	9.5			< 0.001
1	20 %	26	5m 47s	34			< 0.001
2	10 %	6	1m52s	23			< 0.001
2	20 %	26	5m29s	44.9			< 0.001
2	40 %	45	11m12s	85.5	4.41	0.0022	< 0.002
3	10 %	29	6m	32.4			< 0.001
3	20 %	91	28m26s	65.5	4.4	0.0015	0.002
3	40 %	100	33m17s	138	22	0.003	0.0042

Table 1

(*) For tests computed on a P II 450Mhz under Linux with gcc as compiler. The operational program will run on higher performance computing material.

As it can be seen in table 1, the algorithm performance depends on the type and the amplitude of the perturbation factors applied onto simulated SEVIRI data. If these perturbations stay in a range inferior to 40%, stop criteria are reached after an acceptable CPU time (according to the used material). On the contrary, process convergence slows down dramatically when input fluxes are perturbed more than 40 %.
These tests allow us to think the RE process will be able to recover high accurate, high resolution fluxes, in near-real time, if the real spectral modelling differences, the real calibration differences and perturbations due to time and geolocation co-registration between SEVIRI based estimations and GERB measurement, are inferior to 40 %.

6. CONCLUSION

In the frame of the RMIB GERB ground segment processing mission, the last step, called the Resolution Enhancement (RE), is aiming to improve resolution of the accurate fluxes computed by combination of well-calibrated GERB broadband data with SEVIRI narrow-bands high-sampling-rate data, from GERB footprint resolution up to a 3*3 SEVIRI footprint resolution.
Since this RE problem is initially under determined, extra smoothing constraint are added. Then the well-defined problem is expressed as a generalised Lagrange function to minimise and numerically implemented using an iterative scheme based on the Lagrangian gradient calculation.

This iterative Lagrange method was first developed and validated on a simplified problem with modelled data. Gradually, we complicated the problem, checked it with more realistic input images and refined parameters values and algorithm options.
Finally, the algorithm was tested and optimised for input GERB and SEVIRI data simulated from Meteosat 7 measurements. The computing time and memory requirements were checked and performance limitations were analysed.
We conclude we can reach a good compromise between time-memory requirement, and accuracy of the final flux, if the input fluxes perturbations according to ideal fluxes are lower than 40%.

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