SATELLITE ATTITUDE INSTABILITY EFFECTS ON STEREO IMAGES

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ABSTRACT

This paper describes an original method to identify microvibrations of satellites platforms using only a pair of stereo images. Image pairs contain a twofold information: the landscape details and the platform microvibrations corruptions (roll, pitch and yaw). We propose identification methods in the case of a push-broom acquisition mode with a 6000 pixels CCD linear array (case of the french satellite SPOT). This method relies on the image acquisition principle, on the nature of the observed landscape and finally on some concepts of surface geometry. The algorithms providing such identification have been implemented and applied to simulated data, based on a true Digital Model Terrain of Marseille (France). The results of our vibrations identification method are presented here. Comparisons with traditional methods are also presented in this paper.

1. INTRODUCTION

In order to reconstruct a Digital Terrain Model (DTM) in the context of Earth observation by satellite, attitude disturbances of the platform (i.e. microvibrations roll, pitch and yaw) need to be removed from both stereoscopic images before applying the geometric rectification procedure [1-2]. Indeed, spatial environment and/or motion of a mechanical element in the satellite (i.e. platform reaction wheels) produce vibrations. For technical reasons, the on-board feedback loop is not able to apply attitude corrections to the platform when vibrations are in the 0.1 to 100 Hz range, therefore images are corrupted. So, it is is required to identify and separate both effects (attitude perturbations and landscape) directly from the images.

In the case of a stereo image pair, informations contained on each image concern both the landscape and the attitude disturbance. In that context, the inter-correlation is applied to stereo images, providing a ”disparity map” vector field. This disparity map contains the relative disparities due to 1) the attitude variations, and 2) the landscape recorded from two different directions (e.g. one sensor array looks straight downwards and the other one looks with an inclination to the right) [3].

We use these disparities to identify and remove the shifts introduced by the platform microvibrations from the disparity map, and thus to separate vibration disturbances from the landscape information. Cleaning the disparity map represents an essential step before the final process which consists in the topographic 3D coordinates retrieval [4].

One of the main difficulties when separating microvibrations from landscape informations is that the correlation computation is not precise enough to obtain ”true” disparities stereo images. Thus, inherent correlation errors must also be taken into account in the method. So, each vector of the disparity map is a combination of three effects: platform microvibrations, landscape and correlation noise. In this paper, we focus on the first step which consists in the separation of microvibrations disturbances from landscape information. The correlation noise will be considered in a later step.

2. DISPARITY IMAGES ANALYSIS

Instead of analyzing a disparity map, an usual way is to project each vector onto both vertical and horizontal axes, in order to obtain two disparity images. Traditionally, in the case of a push-broom acquisition mode (SPOT4 for example where a linear array of detectors scans the Earth), disparity images are reduced into two unidimensional signals. Each scalar element of these signals represents the mean of each line of a disparity image, and both signals are orthogonal. The components in the direction of satellite displacement (signal called ”mean column”) give information about pitch, those in the direction of satellite’s linear detectors array (signal called ”mean line”) give information about roll. Until now, only these unidimensional signals were used to identify the microvibrations. However, such a method is not efficient for parsing the signal into microvibrations and landscape contributions [5].

Here we propose a two-dimensional global approach based on the disparity images. The following figures (Figs. 1 &2) correspond to simulated disparity images provided by the CNES (french spatial agency). All disparity images used in this paper correspond to the ”true” disparities (i.e. no images correlation, no noise).

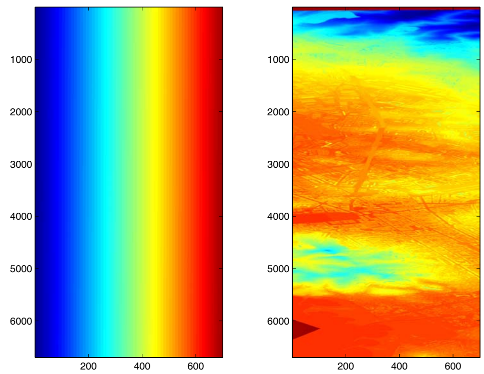

Fig. 1. Reference disparity images of Marseille (France): projections of disparity map without micro-vibration onto the horizontal axis called Line disparity image (left) and the vertical axis called column disparity image (right). Notice that on the left image a ”slope effect” exists because of roll within attitude for one of the two CCD arrays.

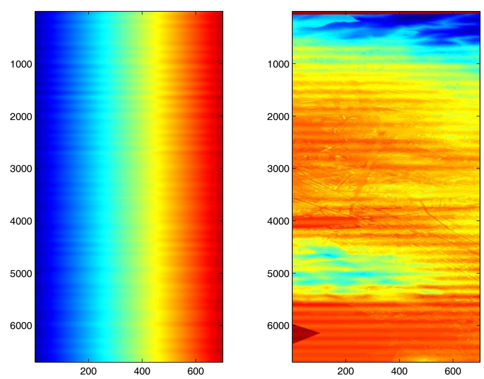

Fig. 2. Projections of the disparity map from Marseille (France) with three nonstationnary vibrations onto horizontal (left) and vertical axes (right).

3. PITCH IDENTIFICATION

We propose a method based on the ”flat points”. It relies on one essential property: flatness is preserved for each flat element of the landscape when the platform vibrates in pitch. Thus, for each line of the column disparity image we take the flat areas. Then, we look for the same areas in the following or preceding line (see fig. 3) and we only keep the common areas of both lines. As the distance between common flat areas of two successive lines is only due to the pitch (and not to the landscape since it is flat), the median of that distance yields the value of the pitch at a given line (or time t_i). Processing the entire image provides the pitch estimation for all recording times t_i.

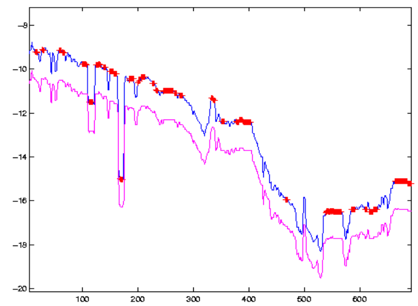

Fig. 3. Representation of a line of the column disparity image. Magenta: without vibration. Blue: with vibration. The red dots correspond to the flat areas. The median of all distances between common flat areas of successive lines is a suitable estimator for pitch.

In this method, the vibration phase is lost, but it is easily retrieved from the ”mean column” signal of the column disparity image. The true amplitude of the pitch is not found by this method, because of the relative character of the process. However, the ratio of the ”mean column” signal variance to that of the estimated pitch provides correct amplitudes retrieval (see Fig. 4).

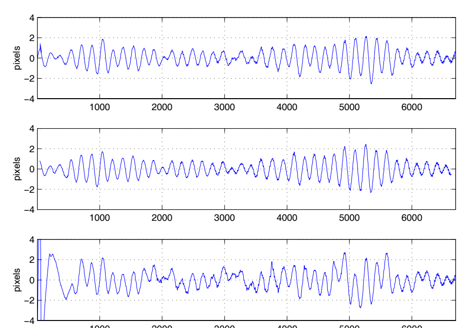

Fig. 4. Pitch identification. True pitch (top), pitch estimated by our method with corrected phase (middle), pitch estimated by the traditional ”mean column” method (bottom).

4. ROLL IDENTIFICATION

We propose a method based on the analysis of slope variations around a mean position. The Line disparity image

(Fig 2 on the left) consists of landscape effects added to a tilted plane. This plane is the effect of the tilted sensor array, so each pixel on the array records different sizes of ground areas (parallax effect). The slope is actually a given line of the Line disparity image. Since each line of the image corresponds to the given recording time t_i, using successive lines provides the variation of the slope. Under the assumption that the slope position of the image without vibration corresponds to the mean of all the slopes positions of the image with vibrations, a *(*mean slope) of the Line disparity image with vibrations can be computed. Then, we calculate a distance between each line and this *(*mean slope). Each slope is not exactly parallel to the others because of residual effects of the landscape and also of a weak yaw effect, so we will rather consider the linear fit of each slope of the "line disparity" image with vibrations (see Figs. 5 & 6).

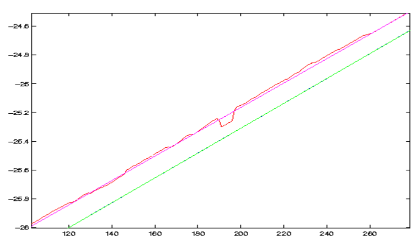

Fig. 5. Example explaining the roll identification principle (here by considering 200 columns of the Line disparity image). Slope of the Line disparity image with vibrations (red) moves beside and below the slope of the Line disparity image without vibration (green). Linear fitting of the red slope (magenta); its oscillations around the green slope provide roll.

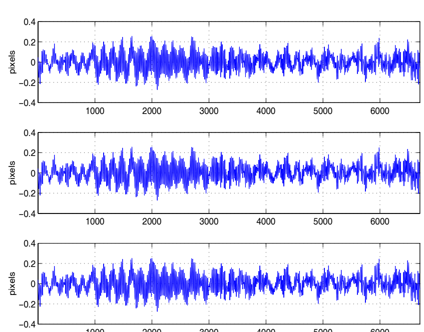

Fig. 6. Roll Identification. True roll (top), roll estimate by our method (middle), The phases and amplitudes are exactly restored by the method.

5. YAW IDENTIFICATION

Traditionally, yaw identification using image processing fails because of the presence of landscape information in the disparity images. Some concepts of surface geometry may help us to identify it [6].

For each satellite revolution around the Earth, the CCD array describes a surface S_i (non-flat and projected onto the ground), where index $i = 1, 2$ corresponds to both passages. This surface is entirely determined by its metric which is defined by $ds_i^2 = E_i\,du^2 + 2F_i\,du\,dv + G_i\,dv^2$. Here u and v are respectively the coordinates in the direction of the detector array and in the direction of the the satellite displacement. The functions E, F and G can be expressed in terms of vectors tangent to the surface S_i. It is then possible to express the attitudes with these metrics.

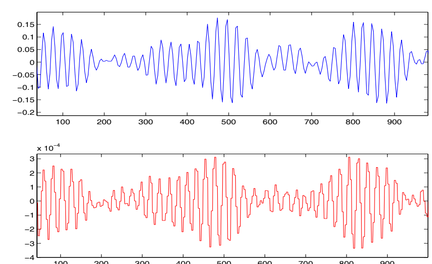

Fig. 7. Part of the yaw identification (first 1000 points). True yaw (top), yaw estimate by our method (bottom).

More explicitly, let the satellite be located with its geographic coordinates (x_i, y_i, z_i), the image is described by the vectorial function:

$$f_i(u,v) = (x_i(u,v),\ y_i(u,v),\ z_i(u,v))$$

The z coordinate could be a Digital Terrain Model. The following functions determine the metric on the surface S_i and give access to the area elements on this surface:

$$E_i = \left|\left|\frac{\partial f_i}{\partial u}\right|\right|^2, \quad F_i = \left(\frac{\partial f_i}{\partial u} \mid \frac{\partial f_i}{\partial v}\right) \ \text{et}\ G_i = \left|\left|\frac{\partial f_i}{\partial v}\right|\right|^2$$

A link can be established between the disparity image and the metric (i.e. to the functions (E_i, F_i, G_i)). So, the metric is linked to the attitude variations. In particular, the variation of the vector $\frac{\partial f_i}{\partial u} \wedge \frac{\partial f_i}{\partial v}$ which is normal to the surface, describes roll and pitch. Yaw vibrations may be provided by the scalar product F_i. On Fig. 7, the term f_i is considered as the elements of Line disparity image , and the mean column of this scalar product is plotted. At this stage, phase and absolute amplitude are not retrieved.

6. CONCLUSION

Results after removing roll and pitch from disparity images are presented on figure 8 (to be compared to Fig 1). Quadratic error for roll estimation is about 0.3% and 4.2% for pitch estimation.

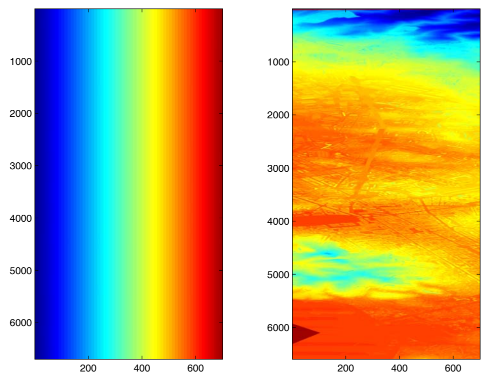

Fig. 8. Line disparity image (left) and column disparity image (right) in which roll and pitch have been removed. Results have be compared to the ”true” disparity images on Fig. 2.

A later study can help us to analyze the estimated vibrations. A Matching Pursuit algorithm [7] provides a set of vectors whose sum matches pitch or roll signals as well as possible. Each vector comes from a single real even function which is dilated, modulated and shifted, which is chosen from a redundant finite dictionary of time-frequency waveforms. The dictionary elements are defined as wavelets, but all the parameters (dilatation scale, shift, frequency modulation) can vary at the same time. On Fig 9, the time-frequency analysis of the estimated roll is presented. A ”chirp” can be identify on this signal.

High resolution space imaging is today in a strong competition context and requires expensive instruments. The spectacular increase of international Earth observation metric resolution satellites leads to significant changes in the conception of optical Earth observation. For satellites in the optical domain, the post-processing reaches an importance comparable to the instrument itself. Indeed, the image restoration algorithmics have reached a sufficient maturity to be computed in the operational phase. Hence, instruments costs soar at an order of magnitude over post-processing costs. This considerable industrial stake leads in particular to a reconsideration of the platforms attitude characterization off-time.

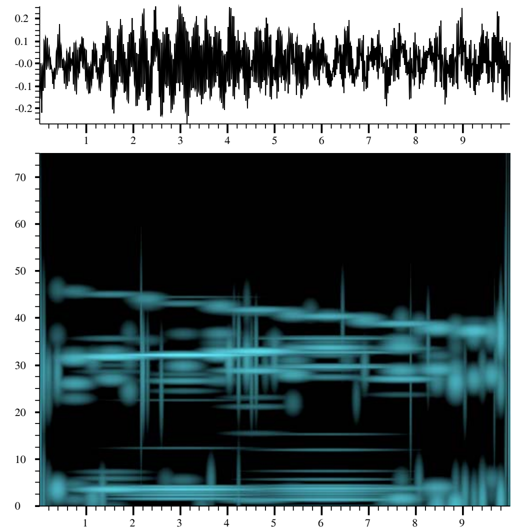

Fig. 9. Example of a time-frequency analysis of the estimated roll. Each grey level represents the energy density of each element. Horizontal axis is time, vertical axis of bottom graph is frequency (s^{-1}). See [8] to download this software.

7. REFERENCES

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