デブリ軌道アーカイブの逆問題的解析と微光デブリの 追跡に関する研究紹介

Researches on inversion analyses of debris orbit archive and tracking of faint debris

○上津原正彦, 樋口知之(統計数理研究所)

OMasahiko Uetsuhara, Tomoyuki Higuchi (The Institute of Statistical Mathematics)

スペースデブリの画像や軌道の時系列データを解析する上で統計的手法は必須である. 今後, 光学センサ やレーダーなどのデブリ観測システムの性能向上によりデブリに関する時系列データのもつ情報量が爆発 的に増加することが予想されることから, 統計的手法の応用は更に重要となる. 本発表では, 著者が取り組 んでいる大量のデブリ観測データを解析する研究について2つのトピックを紹介する. 1つ目は, 低軌道デブ リの軌道を記録している米国 NORAD のカタログを利用した研究である. 本研究ではカタログに記録された 低軌道デブリの平均運動変化率データを用いて, 低軌道物体の高度低下率を一時的に増大させる要因で ある地磁気嵐由来の超高層大気変動の特徴を明らかにしようとしている. 2 つ目は, 時系列画像上に映った 微光デブリを追跡する研究である. 本研究では, CCD/CMOS カメラで捉えた微光デブリを逐次的に効率良く 追跡するアルゴリズムの確立を目指している.

Space debris observation data will be explosively increased as sensor performance improvements in near future. This presentation introduces two topics about big data analyses of space debris observation data. The first topic is an inversion study utilizing NORAD catalog to characterize upper atmospheric fluctuations induced by geomagnetic storms. The second topic is a development of sequential tracking algorithm for faint debris images taken by optical sensors.

Researches on inversion analysis of debris orbit archive and tracking of faint debris

Masahiko Uetsuhara, Tomoyuki Higuchi The Institute of Statistical Mathematics

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Outline

- Space debris observation data will be explosively increased as sensor performance improvements in near future. This presentation introduces two topics about big data analyses of space debris observation data.
- inversion study utilizing the SSN catalog to characterize upper atmospheric fluctuations induced by geomagnetic storms
- 2. development of sequential tracking algorithm for faint debris images taken by optical sensors

Inversion study utilizing the SSN catalog to characterize upper atmospheric fluctuations induced by geomagnetic storms

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Motivation and objective

- Making use of space debris as in-situ sensors of upper atmospheric fluctuations of several days time scale induced by geomagnetic storms
 - Orbit time series of LEO debris in the SSN catalog (i.e., TLE) can be such in-situ measurement data
 - SSN catalog archives thousands of LEO debris orbit time series with (semi-)daily frequency
 - e.g., >1400 LEO debris are archived in 1998 with 0.5~1 day period
- For better understanding of the mechanism of upper atmospheric fluctuation, this study aims at establishing inversion methods which make full use of information in the TLE data of LEO debris

Research overview



Relationship between geomagnetic storm and orbital decay

Storm-driven upper atmospheric fluctuation results in the sudden orbital decay of LEO debris. The sudden orbital decay is recorded in the time series of the mean motion change rate dn/dt [rev/day²].



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Subject of this work

In this work, we conduct cross correlation analysis between Σ Kp and dn/dt of LEO debris to estimate the spatial-temporal pattern of the sudden orbital decay during a storm phase on the late September 1998.



Analysis scheme

For each LEO debris we evaluate the optimum lag (I^*) at which the cross correlation coefficient becomes maximum



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Statistics of debris orbit data applied to cross correlation analysis

- · 1130 LEO debris are available during the event period
- · We regard the orbit at the I* epoch of each debris as its representative orbit



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Cross correlation coefficient of I*

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Cross correlation analysis result

- Alt. 500-700km & incl. 80deg region respond to ΣKp with 1.5~2 day lag
- Alt. 700-800km & incl. 70deg 100deg region respond to ΣKp with 3~5 day lag •

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Cross correlation analysis result



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Summary and future works

- This work estimated time lag of dn/dt to ΣKp during a storm period in the late September 1998 for each of 1130 LEO debris
- When mapping the estimation result into the altitude-inclination space, it was found that debris passing through polar region at mid altitudes first respond to the storm with 1~2 days lag then debris in lower/higher altitudes and lower latitudes
- Future works will include
 - · mapping to the inertial space and/or geomagnetic coordinates
 - establishing an estimation scheme based on the state space model (data assimilation)
- Acknowledgement
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Development of sequential tracking algorithm for faint debris images taken by optical sensors

Background

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• CCD \rightarrow CMOS

- Readout time of CMOS is very rapid (100x CCD) and epoch registration accuracy is very precise (100x CCD)
 →Tracking of O(1deg/sec) debris will become easier for small FOV telescopes & Orbit determination accuracies will be improved
- R&D topics on CMOS camera for debris observation: Sensor design • Detection method • Orbit determination • Sensor operation...
- Enthusiastic trend of applying ground-based optical sensor network for space debris monitoring
 - SSN, ISON, Asia-Pacific networks, ComSpOC, etc...

Objective

This study aims at establishing a faint debris tracking method which is

- capable of handling a large number of sequential images such as CMOS camera's images
- customizable for a variety of observation plans

 \rightarrow Tracking states (position and velocity) of faint debris in image sequences based on the state space model consisting of motion model & observation model

- Motion model describes motion of targets to predict the states
- · Observation model evaluates the "debris-ness" (likelihood) of predicted states



- A single faint GEO debris appears in each sequence
- Image size is 300×300px cut from 2k2k original images
- Image reductions are applied beforehand (bias & vignetting correction · star masking)
- Presence of each target has been double-checked by the JAXA FPGA stacking method

Motion model $\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{v}_k)$

The motion model describes time evolution of state vector \mathbf{x} during a time step assuming target's motion is linear. Uncertainties of position and velocity are also considered.

$$\mathbf{x}_{k} = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{v}_{k})$$

$$x_{k} = x_{k-1} + \Delta t_{k} s_{k-1} \cos \theta_{k-1} + v_{x,k}$$

$$y_{k} = y_{k-1} + \Delta t_{k} s_{k-1} \sin \theta_{k-1} + v_{y,k}$$

$$s_{k} = s_{k-1} + v_{s,k}$$

$$\theta_{k} = \theta_{k-1} + v_{\theta,k}$$



 $\mathbf{Q}=\operatorname{diag}[\tau_x^2 \tau_y^2 \tau_s^2 \tau_{\theta}^2]$

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Observation model $w_k = h(\mathbf{y}_k | \mathbf{x}_k)$

The observation model evaluates the likelihood w_k of the current state \mathbf{x}_k with respect to the current image \mathbf{y}_k



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Tracking algorithm (Particle Filter, PF)

- Motion model and observation model are nonlinear \rightarrow solve by the particle filter
 - 1. Sampling N initial particles from the initial distribution $\{\mathbf{x}_0^{(1)}, ..., \mathbf{x}_0^{(i)}, ..., \mathbf{x}_0^{(N)}\} \approx p(\mathbf{x}_0)$

Repeat the following procedures for each image (k = 1,...,T)

- 2. Prediction; $\mathbf{x}_{k^{(i)}} = \mathbf{f}(\mathbf{x}_{k-1}^{(i)}, \mathbf{v}_{k^{(i)}})$
- 3. Likelihood evaluation; $w_k^{(i)} = h(\mathbf{y}_k | \mathbf{x}_k^{(i)})$
- 4. Resampling; $\mathbf{x}_{k^{(i)}} \sim \{..., \mathbf{x}_{k^{(i)}}, ...\}$ with prob. $\{..., \beta_{k^{(i)}}, ...\}$ where $\beta_{k^{(i)}} = w_{k^{(i)}}/\Sigma(w_{k^{(i)}})$

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Initial state search algorithm (Evolutional Algorithm, EA)

- Sometimes the initial distribution $p(\mathbf{x}_0)$ is unknown (or has very large uncertainty) such as in survey observation
 - Modifying PF to apply EA which iterates heuristic search of initial distribution p(x₀)
- Modification plan
 - ➡ To keep initial particles which have "not so bad" likelihood
 - Change the period of likelihood evaluation from image-by-image (short-term) to a set of images (long-term)
 w_k → Σw_k (k=1,...,T)
 - · At the beginning of each iteration, generate initial particles which consist of
 - · the new particles sampled by a uniform distribution
 - the surviving particles resampled by the previous iteration result (= likelihood evaluation result)



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The results of the EA experiments (20 EA itr. then PF)



Summary and future works

- This work proposed a faint debris tracking method which is capable of tracking a single target and confirmed the capability through experiments
- · Future works will include
 - 1. Estimating target presence
 - 2. Tracking multiple targets
 - 3. Refining the initial state search to online estimation
 - 4. Parallel processing
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